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# Three Essays on Network Dynamics and Liminality

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**THREE ESSAYS ON NETWORK DYNAMICS AND LIMINALITY**

A Dissertation Presented

by

DIEGO F. LEAL

Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
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Department of Sociology

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# DEDICATION

para mi mamá

*"To speak a language is to take on a world, a culture (…) The fact that I had been able to investigate so interesting a problem through the white man's language gave me honorary citizenship."* (Fanon 2008 [1956]: 25).

# ACKNOWLEDGMENTS

collaborating in this area in the years to come. From him I learned a lot about work-life balance. I have promised myself I will try to be more like him in the years to come.

Steve Boutcher and Tony Paik were also important mentors. They showed me how friendship can emerge between colleagues. I do not think I will forget our theoretical debates. The fact that they seriously thought about my arguments made me feel like a peer rather than a mere pupil. I hope to be able to provide such a space for my own students.

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A mi mamá, Elizabeth Castro, le debo mucho de lo que soy. Gracias a ella por ser un ejemplo de berraquera. Sé que todos estos años de distancia la golpearon muy duro. Nadie que yo conozco pudo haberse enfrentado a esa soledad como ella lo hizo. La entereza de mi carácter se deriva del de ella, no tengo duda alguna. A mi tía Piedad, Nando, Magda y Julián, gracias por siempre creer en mí. A Alejandra Zaldúa, mi primer amor, le estoy infinitamente agradecido por su amor y apoyo incondicional. Nuestra relación fue la principal víctima de la pobreza que me acosó en Colombia. Resiento mi suerte por ese hecho pero abrigo la esperanza de conservar su amistad. A toda la gente de *latin@s @ happy valley*, espero verlos pronto. Finalmente, a mis parceros en Amherst y Northampton, tanto los niños (Pibe, Caliche, Mario, Santi, Pipe, Cami, Santi, Mati, Dario y Luis) como las niñas (Arlene, Aleja, Pilar, Ana, Itza y Castri), gracias por su amistad. Sin ustedes me habría vuelto loco, ¡esta tesis es de todos!

**ABSTRACT**

**THREE ESSAYS ON NETWORK DYNAMICS AND LIMINALITY**


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This dissertation focuses on the emergence and evolution of social networks by paying particular attention to the spanning of cultural boundaries that segregate actors in the context of specific societies. In particular, I use systems science methods to study the bridging of cultural holes in small and relatively dense artificial societies, as well as in an American high school. I also study the significance of local triadic configurations in giving rise to the highly hierarchical system of aggregate-level migration flows in place in the Americas during the late 20th century. I use the concept of liminality as a way to analyze these disparate social systems. More precisely, I focus on the role of cultural brokers seen as actors at the limen – i.e. at the border – of symbolic boundaries, actors that can act as bridges between culturally disconnected worlds. In this context, this dissertation explains key network dynamics behind two emergent phenomena that are the direct result of liminal agents' behaviors: the diffusion of innovations (Chapters 1 and 2) and a system of international migration flows (Chapter 3). Finally, I also put forward a critical view on brokerage based on different cases mentioned in the literature (e.g. 1.5 generation migrants or multiracial individuals) that show how the spanning of cultural holes can put brokers at an increased risk of being socially and/or psychologically harmed.

**TABLE OF CONTENTS**

# LIST OF TABLES

# LIST OF FIGURES

# INTRODUCTION

*"I, for one, choose to use some of my energy to serve as a mediator."* (Anzaldúa 1999: 107)

In this dissertation I use network science to understand a set of structural dynamics that emerge at the limen, at the border, of prominent symbolic boundaries. In particular, I focus on emergent phenomena that result from people's behaviors at the interstices of "bright" (Alba 2005) symbolic boundaries that are either computationally designed (Chapter 1) or empirically given, like those of gender (Chapter 2) or nationhood (Chapter 3). Liminality and network dynamics are thus the touchstones of this document.

A key assumption in this dissertation is that when individuals have to, or decide to, traverse disparate cultural worlds, their transgressive behaviors become an important means to understand relevant system-level dynamics of the societies in which they are immerse. Indeed, I submit that we can use the structural traces derived from liminal agents' behaviors in order to understand how to make segregated networks more compact (Chapters 1 and 2), or to investigate how the political economy of international migration flows is hierarchically structured (Chapter 3).

This dissertation is eclectic both theoretically and substantially. Theoretically, I draw from scholarship on international migration (Menjívar 2006; Durand and Massey 2010), symbolic boundaries (Anzaldúa 1999; Lamont and Molnár 2002), race and ethnicity (Bonilla-Silva 2002; Alba 2005), culture and networks (Pachucki and Breiger 2010; Lizardo 2014), adolescent friendship segregation (Moody 2001; Goodreau, Kitts and Morris 2009), social simulation (Schelling 1971; Axelrod 1997); social contagion theory (Christakis and Fowler 2013), and the diffusion of innovations (Valente 1991; Centola 2015). The eclecticism of this dissertation is also evident in the heterogeneity of the actual systems under analysis. Indeed, I

study relatively small artificial societies (Chapter 1), an American high school (Chapter 2), and migration flows among all the countries in the Americas (Chapter 3).

Methodologically, I consistently use systems science methods like agent-based models (Chapter 1), stochastic actor-based models (Chapter 2), and temporal exponential random graph models (Chapter 3), in order to characterize the dynamics and evolution of the disparate systems mentioned above. This dissertation can thus be understood as a tripartite document in which network science tools and theories are employed to make sense of the dynamic implications of (cultural) liminality in social systems of varying nature.

The aim of Chapter 1 is to produce a parsimonious computational model in which a bright symbolic boundary is, by design, the source of different levels of cultural segregation. More specifically, I put forward a theoretical model to understand how liminal agents can act as cultural brokers that have the potential to make segregated networks more compact by means of bridging cultural holes (Pachucki and Breiger 2010). In this context, I first develop a critical perspective on liminality and cultural brokerage, always emphasizing that the capacity to span cultural holes is a socially – and usually painfully – learned skill (Anzaldúa 1987; Wang and Collins 2016; Myers and Williamson 2001; cf. Burt 2004). I then combine the principles of consolidation, influence, and selection to generate artificial societies with tunable levels of segregation across a bright symbolic boundary (Blau 1977; Blau and Schwartz 1984; Latané 1981, 1996; Macy, Kitts, Flache and Benard 2003; Centola 2015). After doing so, I simulate diffusion dynamics based on a threshold model (Schelling 1978; Granovetter 1978; Macy 1991). Results show that, due to their cross-cutting ties, cultural brokers are more effective than popular agents (agents with high degree centrality), structural brokers (agents with high betweenness centrality), or random agents, to diffuse an innovation widely. The

interrelationships between culture and social network positions are discussed in the final part of the chapter.

In Chapter 2, I advance an empirical test for the hypothesis that cultural brokers are especially well-equipped to span cultural holes. From a methodological point of view, I build on both published social simulation studies (Shoham et al. 2012; Zhang et al. 2015a, 2015b) and on my previous work with James Kitts, in order to configure an empirically-calibrated agent-based model that mimics the computational experiments developed in Chapter 1. Results show that agents with a high capacity for cultural brokerage across key symbolic boundaries like gender or age do show an enhanced ability to spread an innovation across people culturally different from themselves; thus, allowing them (i.e. cultural brokers) to make segregated networks more compact. I then discuss the implications of the results for the analysis of the spreading of innovations across in-group and out-group alters in light of the critical theory of liminality I developed in Chapter 1. In the final part of Chapter 2 I discuss future lines of work vis-à-vis the idea of liminality and examine the empirical limitations inherent to the research design used in this specific chapter.

Finally, in Chapter 3, I study a liminal population *par excellence*, namely, international migrants (Menjívar 2006; Mann 2016; Huang et al. 2008). More precisely, I advance an unprecedented description and explanation of international migration flows in the Americas based on the network inequalities that sustain them over time. Building on previous work with Joya Misra and Ragini Malhotra (Malhotra, Misra and Leal [2016]), I estimate migration flows between all the countries in the Americas using novel data and state-of-the-art statistical techniques (Özden et al. 2011; Abel 2010, 2013, 2017; Abel and Sanders 2014). I then provide a detailed historic account of these flows by focusing on the following migratory subsystems: Central America and the Caribbean, North America, and South America. Lastly, going beyond

my previous collaborative work, I combine network and migration theories, as well as Temporal Exponential Random Graph models (Hanneke, Fu and Xing 2010; Desmarais and Cranmer 2012b; Liefeld, Cranmer and Desmarais 2017), to explain the evolution of migration flows over time. In particular, I show that international migration in the Americas exhibits very strong network inequalities at the level of triads. These local configurations are a structural signature of the highly unequal nature of the migratory exchanges in the Americas and of the political economy that sustains them.

I conclude the dissertation with a discussion on the implications of my findings for future scholarship on cultural brokerage and network dynamics. In particular, I discuss the role of a critical perspective on brokerage as the foundation for a relational sociology of diffusion dynamics across culturally segregated networks.

# CHAPTER 1

## DIFFUSION AS THE BRIDGING OF CULTURAL HOLES: AN AGENT-BASED

## COMPONENTIAL MODEL

### Introduction

The fact that individuals tend to imitate each other is a fundamental characteristic of human social interactions (Bandura 1977). Importantly, when individuals imitate one another a process of (social) influence is said to take place (Meltzoff 2005; Hurley and Chater 2005; Christakis and Fowler 2011). Influence is by definition a relational process in which at least one of ego's characteristics is shaped or impacted by being exposed to one or more socially immediate alters over a period of time (Latané 1981, 1996). Influence is far from being a random process. Humans deliberately tend to adopt certain behaviors and norms (e.g. clothing style) because they are associated with specific traits (e.g. socioeconomic status) (Galak et al. 2016). It is precisely because of this relational and dynamic nature that the adoption of innovations is a classic topic in the study of network dynamics (Rapoport 1953; Coleman, Katz, Menzel 1957).

People not only influence each other, however. Homophily is another bedrock of human behavior (Lazarsfeld and Merton 1964). Homophily is the tendency to interact with similar (e.g., same-status) instead of dissimilar (e.g., different-status) partners. Put simply, homophily implies that individuals who are already alike tend to select each other as associates (McPherson, Smith-Lovin and Cook 2001; Barnett, Khanna and Onnela 2016). Like influence, (homophilous) selection is by definition a relational process. One partner must choose another based on their preexisting similarities in order for a selection process to occur. Supporting evidence of the tendency of humans to be part of homophilous relationships has been found in very different settings, from gene-set analyses (Christakis and Fowler 2014) to large-scale

interactions in humanity's largest gathering, the Kumbh Mela festival in India (Barnett, Khanna and Onnela 2016).

At the macro level, when selection and influence unfold over time, they can potentially give rise to societies in which the empirical distributions of the different traits exhibited and/or assigned to individuals (e.g. education, race, or religion) are highly *correlated* (Latané 1991, 1996) or, in Blau's (1977) terms, *consolidated*. Critically, given the tripartite forces of influence, selection, and consolidation, the networks of social connections between individuals in a given society typically become a key vehicle to (re)produce segregation (Macy, Kitts and Flache 2003; Centola 2015). In a nutshell, if individuals are inclined to be both selected and influenced by similar others, then more and more positive correlations between their traits (i.e. higher levels of between-individual similarity) are likely to emerge as a result of their interactions. Over time, repeated interactions between similar people tend to crystallize in the form of highly clustered social structures (e.g. social networks); which in turn reinforce and (re)produce clustering; that is, segregation.

A corollary of the ideas mentioned above is that, when an innovation emerges, it is likely to be confined within the boundaries that segregate similar (e.g. same-race) from dissimilar (e.g. different-race) actors in a given social network (DiMaggio and Garip 2011). In a word, networks can be expected to (re)produce high levels of inter-group inequality in the adoption of innovations (DiMaggio and Garip 2001; Centola 2011; Chang and Lauderdale 2009). Given that social networks are proven conduits of information and social support (Barefoot et al. 2005; Santini et al. 2015), differential access to innovations can be highly consequential for individuals' outcomes. For instance, there is strong evidence suggesting that social networks, and particularly the social reinforcement they entail, are causally related to the adoption of health-related innovations (Centola 2011).

Based on that fact that empirical networks tend to be highly segregated, I argue that leveraging the role of culturally liminal individuals might prove crucial to help overcome the powerful societal forces behind segregation. By *culturally liminal individuals* I refer to people located at the interstices of symbolic boundaries drawn along cultural lines (e.g. race & ethnicity, gender, or religion) (Romo 2011; Turner 1967; Wimmer 2013; Malkki 1992). More precisely, I submit that identifying and mobilizing individuals that tend to be located at the cultural interstices of society could make segregated networks more compact by spanning "cultural holes" (Pachucki and Breiger 2010; Lizardo 2014), that is, by bridging people that tend to be located in culturally different worlds.

In this Chapter, therefore, I focus on individuals' capacity to widely diffuse an innovation based on their position as cultural brokers along prominent symbolic boundaries. For ease of exposition, I will tend to use two rhetoric examples throughout this Chapter. First, I will continuously refer to race & ethnicity (i.e. the ethnoracial symbolic boundary) as an empirical reference to connote a symbolic boundary composed of nominal categories along which networks have been observed to be highly segregated (McPherson et al. 2001; Alba 2005; Moody 2001). Second, I will use the classic notion of "adolescent societies" (Coleman 1961) – as it refers to the social structures typically observed in American high schools – as a prominent empirical example of relatively small, well-bounded, societies. This is important because this Chapter focuses on the diffusion of innovation in small societies and adolescent societies have proven to be fertile ground for network diffusion processes (Shoham et al. 2012; Zhang et al. 2015; adam and Schaefer 2016; de la Haye et al. 2011; Moody 2002; Kreager and Haynie 2011). My argument, however, applies to any prominent symbolic boundary along which segregation between a relatively small number of mutually exclusive and nominal group memberships (i.e. $3 \leq$ groups $\leq 10$) takes place and to any relatively small society, not only to

adolescent societies. Furthermore, my argument applies to relatively dense undirected networks in which both social ties and contagion are binary (i.e. a tie between a given pair of actors either exists or does not exist; an actor is either an adopter or it is not); contagion is also assumed to be permanent (i.e. there is no recovery, that is, once an actor becomes an adopter continues to be so until the simulation is over) and local (i.e. non-adopters can only be potentially infected by their immediate network neighbors).

The Chapter is organized as follows. First, I develop a theoretical framework around the idea of liminality. Second, I describe the data and methods that structure the Chapter. Third, I present the data analysis based on a simulation study. Lastly, I discuss some conclusions.

## Theory

### Symbolic Boundaries and (Permanent) Liminality

Symbolic boundaries, like those drawn along race, class, nationality, and gender are of primary interest to social scientists (Lamont and Fournier 1992; Lamont and Molnár 2002; Wimmer 2013; Malkki 1992). Far from being orthogonal, symbolic boundaries very often intersect (Browne and Misra 2003; Collins 2015). Furthermore, symbolic boundaries are not ahistorical, fixed, or natural, they are in fact rather context-dependent and permeable (Mäs, Kitts and Flache 2014; Pachucki, Pendergrass and Lamont 2007).

The idea of liminal populations refers to people located at the interstices of one or more symbolic boundaries, that is, *betwixt and between* them (Turner 1967). In the remainder of this document I will understand liminality as "the state of being associated with people who are simultaneously members of two or more culturally distinct groups, which allow them [liminal individuals] to move beyond an "either/or" to a "both/neither" path of

identification." (Romo 2011: 404). As explicitly noted by Romo, liminality is intimately associated with culture. Liminal agents are, by definition, culturally liminal.

Historically, the concept of liminality has been closely tied with dynamic, rather than static, social phenomena. In his classic book Rites of Passage, Arnold van Gennep (1960 [1909]) describes life as a series of transitions from one point (e.g. childhood) to another (e.g. adulthood). Conceptually, he divided life transitions in three kinds of rites: rites of separation (preliminal rites), rites of transition (liminal rites), and rites of incorporation (postliminal rites). In his work, van Gennep focused on individuals living in small-scale – agrarian or indigenous – communities. Because of this, his theoretical framework is mostly adequate to the analysis of transitions experienced by individuals in traditional societies.

Several decades later, Victor Turner revisited and expanded van Gennep's original concept. Turner connected liminality with people being at the interstices of social structure, an intuition critical for this Chapter: "If our basic model of society is that of a "structure of positions," we must regard the period of margin or "liminality" as an interstructural situation." (Turner 1967: 93). Importantly, and unlike van Gennep, Turner applied the notion of liminality to analyze transitions that individuals undergo in the context of contemporary institutions like professions (Turner 1967), millenarian religious movements, or hippie communities (Turner 1969). It is with the work of Turner, therefore, that liminality starts to be useful to describe contemporary social realities.

By the end of the 20th century, sociologists interested in macro-level transitions started to use the concept of liminality. Liminality was introduced to contemporary sociology by Zygmunt Bauman and S.N. Eisenstadt in order to describe macro-level changes in contemporary societies. On the one hand, Bauman (1992) used the concept of liminality to analyze the intricate transitions experienced by post-communist regimes in the late 20th

century. On the other hand, Eisenstadt (1995) employed the notion of liminality to theorize the emergence of protest groups and movements that were structurally in-between key dominant groups. Still within this macro-level perspective, Szakolczai (2014) used the idea of liminality to study critical societal changes in Ireland at the turn of the 21ˢᵗ century. Importantly, Szakolczai emphasized that liminality can, and indeed had been, used to describe not only temporary societal transitions, but also situations in which societies exhibit a permanent state of flux. That is, times of societal crisis that seem to be extraordinary and/or transitory at the onset, but that become highly routinized in practice (e.g. long-term crisis managed by charismatic leaders; see also Agamben [2005]). Szakolczai (2014) denoted these particular situations as states of *permanent liminality*.

Some of the most recent literature on liminality has returned to the origins of the concept by means of focusing on micro-level, rather than on macro-level, situations. Importantly, nonetheless, the idea of permanent liminality coined by Szakolczai is also prominent in this micro-level literature. Here, however, permanent liminality refers to situations in which individuals – not societies – exhibit relatively permanent in-between or ambiguous characteristics such as those typically associated with gypsy or migrant populations (Clopot 2016; Romo 2011; Anderson et al. 2009; Huang, Yeoh and Lam 2008; Brunsma, Delgado and Rockquemore 2013; Rampton 1999). For instance, a clear intuition of permanent liminality underlays the concept of liminal legality coined by Menjívar (2006). Liminal legality in Menjívar's framework describes the vicissitudes of the permanently uncertain legal status of large numbers of Central American migrants living in the US. In sum, the contemporary literature on liminality does allow for both an individual-level analysis of liminality and, more specifically, for the theorizing of liminal individuals as susceptible of being in a state of permanent liminality.

This Chapter is firmly inscribed in this latter tradition since I understand cultural brokers as individuals living in a state of permanent liminality. Put simply, I argue that the permanent liminality of cultural brokers does not emerge from the fact that they are undergoing a specific – mostly temporary – transition (e.g. transition to adulthood or parenthood). Quite the opposite, their liminality is a result of their positionality along the more or less fixed symbolic boundaries along which society is segregated, and more specifically, a result of their tendency to be connected with people located in different nominal categories (e.g. different racial categories) along such boundaries.

## Cultural Brokerage and Liminality

Not all symbolic boundaries are equally important for the (re)production of cultural segregation in a given society and, therefore, for the emergence of cultural holes. For instance, religious affiliation was more important than skin color (or any other symbolic divide) to define and segregate the (non-Christian) others in the pre-colonial West (Omi and Winant 1986; Bonilla-Silva 1997). In such a specific historical context, I argue that a person at the interstices of the religious boundary likely was both more readily perceived as a liminal individual and better positioned to span cultural holes than a person at the interstices of any other symbolic boundary. Think, for instance, about the role of the pre-colonial Christian missionary: a liminal agent whose job was to find ways to act as cultural translator between different religious beliefs systems, effectively becoming a powerful vector of cultural syncretism (Ferdinando 1995). Prominent Christian missionaries like St. Cyril are indeed critical to understand the development, and diffusion, of innovations like the Glagolitic alphabet, the oldest known Slavic alphabet – and a powerful example of cultural syncretism in the Middle Ages.

An obvious analytical problem in the analysis of diffusion processes across symbolic boundaries is how to parsimoniously account for all the boundaries that effectively shape the sociodemographic (Blau) space along which a given society is culturally segregated.[1] Here, I follow a strategy used by Laumann (1973), and mentioned by Blau (1977: 29), as a possible solution to this problem: select *one* social dimension, "considered on a priori grounds to be of special importance," in order to analyze, and eventually model, key societal dynamics. To address this issue from a theoretical point of view, I rely on the idea of symbolic boundaries' "brightness".

Following Alba (2005), when compared to blurry boundaries, bright boundaries are typically difficult to cross since the symbolic distinctions they (re)produce tend to be perceived as "unambiguous, so that individuals know at all times which side of the boundary they are on." (Alba 2005: 22). A key implication of misrecognizing bright symbolic boundaries as immutable and ahistorical – as "unambiguous" in Alba's terms – is that every-day social interactions tend to become deeply segregated along the lines symbolically demarcated by those boundaries (Fields 1999). For instance, an important reason behind the brightness of the ethnoracial boundary in contemporary Western societies is related to the fact that it is typically misrecognized as rooted in biology (Emirbayer and Desmond 2015; Fields 1999; Bonilla-Silva 1997).

In this Chapter, I focus on cultural brokerage along bright boundaries only. More precisely, I analyze the bridging of cultural holes through the diffusion of innovations championed by cultural brokers situated at the limen, at the (cultural) border, of a bright boundary. All this in the context of relatively small, well-bounded, societies generated through

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[1] By sociodemographic (Blau) space I mean the multidimensional distribution of individuals' traits like race & ethnicity, gender, class, religion.

social simulation methods. An empirical referent close to this kind of ideal scenario in which one symbolic boundary is widely known to be preeminently correlated with segregation dynamics in relatively small, well-bounded, societies is that of segregation along the ethnoracial line in American high schools. The studies that support this empirical reference are legion (Hallinan 1978; Hallinan and Williams 1987; Joyner and Kao 2000; Moody 2001; Giordano 2003; Quillian and Campbell 2003; Mouw and Entwisle 2006; Zeng and Xie. 2008; Goodreau et al. 2009).

## Towards a Critical View of Liminality

Before analyzing the spanning of cultural holes along bright symbolic boundaries (hypothetically) championed by cultural brokers, a critical view of cultural brokerage, and of liminality more generally, is warranted. This is especially true since being able to present oneself as belonging to a group – as being *in*, instead of *in-between* – offers a wealth of advantages. The sense of belonging (i.e. again, of being *in*) is in fact a proven source of stability, well-being, and success (Hurtado and Carter 1997; Faircloth and Hamm 2005). In this section, I develop a set of arguments, rooted in the experiences of liminal subjects, in order to advance a nuanced and critical perspective on the burdens of (permanent) liminality. I present these arguments in the form of three critical qualifications associated with the realities confronted by liminal individuals.

### <u>Do not Romanticize Liminality</u>

Gloria Anzaldúa's Borderlands/La Frontera (1987) is perhaps one of the best known contemporary pieces on liminality. In her book, Anzaldúa describes the life of migrants in a liminal geographic space, namely, Aztlán (the 'borderland' between Mexico and the US Southwest). When international migrants cross over a national border, Anzaldúa argues, they

are also crossed over (*atravesados*) by that very same border. This condition of liminality is experienced by migrant populations like international migrants, internal migrants, refugees, and gypsies (Mann 2016). Anzaldúa powerfully references this state of permanent liminality:

> "A borderland is a vague an undetermined place created by the emotional residue of an unnatural boundary. *It is a constant state of transition*. The prohibited and forbidden are its inhabitants. Los atravesados [the crossed over] live here: the squint-eyed, the perverse, the queer, the troublesome, the mongrel, the mulato, the half-breed, the half-dead; in short, those who cross over, pass over, or go through the confines of the "normal"." (Anzaldúa 1987: 3, emphasis is mine).

Liminality cannot only be an immense burden, as Anzaldúa argues, it can also be a highly viscid one. For instance, liminality does not usually die with those who initially transgress the symbolic boundaries of nationhood, the so-called first generation migrants. Liminality gets transferred to their offspring, and the offspring of their offspring. In fact, Anzaldúa provides accounts of fifth generation Mexican Americans living in the borderland that are still repeatedly deported to Mexico due to their phenotype.

The concept of transnational family (Parreñas 2005) also incarnates the complexity of liminal identities. A transnational family is comprised of members located in two or more nation states. Transnational families typically encounter patent difficulties like those associated with the recurrent sense of loss experienced by the children that are left behind in the country of origin by their parents, especially by their mothers. "Transnationals, and their family members often grapple with a sense of liminality –a state of ambiguity, openness and indeterminacy of identity– as they negotiate their transnational life courses." (Huang et al 2008: 7). The notion of transnational families has indeed been used to make a call to expand the notion of family itself since the literature often assumes that family members enjoy the advantages of physical proximity (Mazzucato and Schans 2011).

Perhaps one of the most complex links between liminality and disadvantage is embodied in the experience of refugees and displaced peoples. To be sure, refugees have been

repeatedly conceptualized as liminal agents (Malkki 1992; Williams 2006; Chavez 1992). Their resettlement in the host society is usually traumatic, which might partially explain why refugees tend to be affected by mental health disorders (Fazel, Wheeler and Danesh 2005). In this regard, Weil powerfully argues (1987: 41, cited in Malkki (1992: 24): "to be rooted is perhaps the most important and least recognized need of the human soul." The case of refugees is without a doubt a reminder that a state of permanent liminality is not necessarily free of burdens (Williams 2006).

In the literature on adolescent friendship segregation, there is also evidence that guards against a purely romanticized view of liminality. A recent study by Boda and Néray (2015) collected data from a sample of non-Roma Hungarian and Roma Hungarian secondary school students. They found that both minority and majority students tend to dislike students with inconsistent ethnic identifications, that is, students for whom *self-declared* vs. *peer-based* ethnicity identification do not coincide. This finding is important because it reminds us that exhibiting ambiguous (ethnoracial) identities could represent an important social burden for individuals.

In conclusion, being at the interstices of a given social structure is far from being a purely positive trait (cf. Burt 2004). More precisely, those who are in-between bright symbolic boundaries, like those of race & ethnicity, citizenship, or nationhood, are certainly at risk of experiencing the negative effects of liminality (e.g. exclusion, isolation, mental health disorders etc.). Moreover, permanent liminality does not necessarily end with the liminal persona. It can, for instance, easily extend over the course of several generations.

**Do not Naturalize Cultural Brokerage**

Bridging culturally different others should not be misrecognized as a natural talent of liminal individuals. Here a powerful empirical case is that of the so-called 1.5 generation migrants (Ang 2001). This subset of international migrants is typically comprised of

adolescents that migrated with their parents during their early teens. Indeed, 1.5 generation

migrants are culturally hybrid by definition since they live in culturally dualistic realities, shaped

by the culture (e.g. the language) of the origin and host societies. To be sure, these migrants

have been explicitly conceptualized as in-between or liminal individuals in the past (Wang and

Collins 2016; Bartley and Spoonley 2008). Critically, Wang and Collins (2016) provide

qualitative evidence of how 1.5 generation Chinese migrants in New Zealand bridge cultural

differences with white European New Zealanders (Pākehā) through cosmopolitan cultural

norms. The authors emphasize, however, that the 1.5 generation migrants they study do not

have an inherent ability to negotiate cultural differences. Rather, this ability emerges from the

fact that 1.5 generation migrants are permanently exposed to racialized interactions vis-à-vis

the dominant group precisely because of their cultural in-betweenness (see aslo Myers and

Williamson [2001] for evidence on the vicissitudes of Latinos as "interlopers").

In a similar vein, Emirbayer and Desmond (2015) discuss the idea of multiracial

competence. Here they have in mind "skilled code switchers" who can traverse racial

boundaries with certain ease. They, for instance, mention "the Mexican American executive

who excels in the majority-white corporation but who speaks Spanish at home." (Emirbayer

and Desmond 2015: 175). The authors readily emphasize the idea that this cultural "code

switching" (e.g. voice inflections, 'passing'), and the multiracial competence it entails, is socially

learned.

Further, albeit relatively indirect, evidence of how cultural brokerage is a socially

learned skill rather than an innate "talent" of cultural brokers comes from the literature on

socialization patterns of adolescents. Edmons and Killen (2009), for instance, found that

parental racial attitudes affected interracial friendship formation in their children. They based

their findings on a sample of racially diverse high school students located in the U.S. Mid-

Atlantic region. The authors found that negative parental racial attitudes were associated with lack of intimacy in their children's interracial relationships. Similarly, in a study of German and Dutch students, Smith, Maas, and van Tubergen (2014) found that adolescents' cross-ethnic relationships were unlikely to emerge when their parents did not act as role models themselves. More precisely, Smith et al. (2014) found that adolescents tended to have more inter-ethnic relationships when their parents were less willing to maintain in-group traditions or more willing to have out-group friends themselves.

In sum, bridging cultural holes is typically difficult – and even painful – to learn and perform effectively. The case of 1.5 generation migrants, as well as the literature on socialization and cross-ethnic relationships prevent us from assuming that liminal individuals are naturally inclined to bridge cultural holes, that is, to act as cultural brokers – especially along bright symbolic boundaries. Put simply, bridging cultural holes is a social skill rather than an innate talent. Finally, bridging cultural holes is also a difficult task since it likely involves negotiation of cultural difference in situations where liminal agents typically have to interact with higher status peers that might likely see them as inferior due to their symbolic hybridity; they are the "outsiders within" (Collins 1986).

### Do not Universalize Bright Symbolic Boundaries

Bright boundaries are symbolically and socially constructed and because of that heavily context dependent (Omi and Winant 1986; Lamont 2000). For instance, the fact that race is a bright boundary in the US does not mean a) that this is also the case in other latitudes; and/or b) that the way race is experienced in the US is universal. In the context of this example, a corollary of this argument is that racial liminality could be especially important to bridge cultural holes in the US but not in other places. Alba (2005) for instance, argues this is the case in France and Germany where the discourse of difference typically discards the notion of race.

Another compelling argument about the relativity of bright symbolic boundaries comes from the works of Davis (1991) and Telles and Sue (2009). According to these authors, racially liminal individuals can have different status depending on country and time. They argue, for instance, that in Korea, Korean Americans have *lower* status compared to their non-liminal counterparts; that mulattoes in pre-1960 Haiti had *higher* status than their non-liminal counterparts; and that mulattoes' status in Colombia and Brazil is *highly variable*, depending more on class than on skin color (see also Telles and Paschel 2014).

Liminality in general, and the status attached to it in particular, is not universal across countries, nor is universal across the history of a given country. For example, different rules to classify multiracial people – especially multiracial individuals of African descent – have been used in the US for centuries (DaCosta 2007). The dynamism of racial classifications is key to remember that bright symbolic boundaries are not material or fixed, and because of that, should not be reified. For instance, at certain critical junctures, some liminal individuals accrue honorary tickets to enter the dominant group, which in the long run reinforces racial boundaries by keeping symbolic distinctions (e.g. Us versus Others) very much alive. We know, for example, that white as a racial category was expanded over the course of the 20th century to include second and third generation Irish and Italians (Alba and Nee 2009; Portes and Rumbaut 1996). More recently, the Latin Americanization thesis (Bonilla-Silva 2002; 2004) argues that the racial hierarchy in the US is now tripartite (whites, honorary whites, and collective blacks), rather than bipartite (whites & non-whites). Experimental evidence on influence processes in task-oriented groups strongly supports this hypothesis (Biagas and Bianchi 2015).

In sum, I argue that liminality is not universal in two main ways. First, the definitive centrality of specific bright boundaries in a given society does not always hold in other

societies. Even more, when – nominally speaking – the same boundary has attained the same preeminence or brightness in two different societies (e.g. race in Brazil today vs. race in the US today, or race in the US today vs. race in the *antebellum* US), the meaning and consequences of liminality and cultural brokerage likely differ a great deal. Second, the classifications on which symbolic boundaries, and therefore liminality, rest are fluid. For instance, racial hybrids in one society might not even be considered hybrids in other society, or have the same privileges attached to them. In a word, the primacy, meaning, and consequences of specific symbolic boundaries, and of liminality and cultural brokerage in particular, are not universal. They are, in fact, context- and time-dependent and could affect actors positively or negatively. Any empirical analysis of cultural brokerage must, therefore, be highly aware of the relativity of liminality and cultural brokerage.

Throughout this section I have tried to define liminality and the cultural brokerage hypothetically performed by liminal agents. Now, I have enough theoretical traction to revisit the key tenet of this Chapter: liminal individuals have higher potentials to span cultural holes, that is, to make segregated networks more compact by bridging people of different cultural backgrounds. In the following section I turn to describe the data and methods I use to analyze this tenet.

### **Methods: Measures & Description of the Computational Model**

I contribute an explanation to the existing literature on the diffusion of innovations by studying the bridging of cultural holes using agent-based computational models (Schelling 1971; Axelrod 1987; Epstein and Axtell 1996; Carley 1991; Macy and Willer 2002; Mark 2003; Kitts 2006a). In particular, I will model the diffusion of an innovation by paying particular

attention to the brokering capacity of agents at the interstices of a bright boundary, that is, a boundary along which the sociodemographic (Blau) space of a given society is segregated.[2]

**Measuring Cultural In-Betweenness: The Capacity for Intercultural Brokerage**

Based on the work of Gould (Gould 1988, Gould and Fernandez 1988), I developed a measure of agents' capacity for intercultural brokerage. I argue that this measure could be thought of as a proxy of cultural in-betweenness (i.e. liminality,) that is, of the degree to which an agent occupies a boundary-spanning position in the context of a social structure that is highly segregated along a bright symbolic boundary. The rationale for my measure is simple: I aim to develop a measure to identify egos that have a higher potential to bridge alters situated at different sides of a bright boundary; alters that are otherwise socially disconnected precisely because of the level of segregation exhibited by their (cultural) worlds.

I define the capacity for intercultural brokerage of agent j (i.e. the broker/ego) as the total number of two-step undirected paths between two alters of two culturally different groups (i.e. the 'terminal' nodes of the two-step path) on which agent j happens to be the 'internal' node of the two-step path. These are, effectively, triplets with two ties present and one tie absent – the famous forbidden triad of Granovetter (1973) – in which the disconnected nodes of the triad belong to two different groups. In instances in which a given pair of culturally dissimilar alters are connected through more than one broker/ego, the capacity for brokerage of each individual broker/ego between the alters under consideration increases by $1/p$, where p is the total number of brokers between the alters. As shown in the robustness checks section, the results discussed in this paper do not mechanically depend on the mere number of two-step undirected paths in which a given agent acts as a broker; it is an agent's

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[2] On the idea of Blau space see McPherson (2004). For a recent theorization and operationalization see Brashears, Genkin and Suh (2018).

capacity to bridge disconnected actors of *different* groups that explains the diffusion patterns observed in this paper.

Assuming everything else is constant, I argue that the higher the number of instances in which an ego bridges culturally dissimilar *and* disconnected alters, the higher ego's cultural in-betweenness and, therefore, ego's potential to act as a cultural boundary-spanner. Formally, I define an ego's capacity for intercultural brokerage $IB_j$ as follows:

$$IB_j = \sum_{i=1;i<j}^{n} \sum_{k=1}^{n} \frac{b_{(ijk)}}{p_{(ik)}} * m_{(ik)} \qquad (p_{(ik)} \neq 0, i \neq j \neq k)$$

eq. 1

Where $b_{(ijk)}$ is equal to 1 if actor i is connected to j, j is connected to actor k, and actor i is not connected to actor k, and 0 otherwise; $p_{(ik)}$ is the number of two-step undirected paths between i and k, and $m_{(ik)}$ equals 1 if i and k are from different cultural groups (e.g. racial groups, if the focus is on interracial brokerage), and 0 otherwise. A hypothetical graphic example of this measure is presented in Figure 1.1.

In Figure 1.1, all actors are culture blue, except actor C. Actor F gets a brokerage score of 1 because she brokers the relationship between G and C, while no other actor connects G and C. On the other hand, actor E gets a score of 0.5 because she brokers the relationship between D and C, but she is not the only broker between these two actors (D and C); indeed, B also brokers the relationship between D and C. Finally, actor B gets a total score of 1.5 since she co-brokers the relationship between D and C (0.5), and she is the only broker between A and C (1).

Critically, the capacity for intercultural brokerage represents a methodological advancement in terms of how to approximate the idea of bridging cultural holes, which is in itself a contribution to the literature since the theory of cultural holes did not provide concrete

measures in its original formulation (Pachucki and Breiger 2010; but see Lizardo [2014] on how to measure cultural omnivorousness).

**Description of the Model: Generating Segregated Societies along a Bright Boundary**

A critical component of my analysis is to simulate social structures with theoretically informed, and fully tunable, levels of segregation based on nominal group distinctions. In order to do so, I follow Centola's (2015; for an earlier formulation see Macy, Kitts, Flache and Benard [2003] and Latané [1981; 1996]) intuition in terms of modeling a society's overall network structure as the result of the interaction between two forces: consolidation and homophily (Appendix A.1.1 presents the pseudo-code of the simulation program; the actual program is available at www.diegoleal.info).

I take two steps to model consolidation. First, after populating the model with a given number of agents (**N**), each agent is bestowed with a nominal group membership (**G**). The number of possible groups has to lie in the following range $2 \leq \mathbf{G} \leq x$ where $\{x : x \in [3,\infty)$ and $x \in \mathbb{Z}^+\}$ and $\{\mathbf{G} : \mathbf{G} \in \mathbb{Z}^+\}$. Once **G** is chosen by the user, each agent is randomly assigned to one, and only one, of the possible groups. I denote the resulting distribution of agents within groups as the *primary boundary* (**PB**). The more groups there are, the more "heterogeneous" the society is said to be (Blau and Schwartz 1984). Assume, for instance, that each agent in a hypothetical society is assigned a value in a tripartite racial categorization (e.g. white, black, or brown). The distribution of these three group categories across all agents would represent the primary boundary in this hypothetical society. The primary boundary always remains unchanged throughout the simulation process.

Second, a set of *secondary boundaries* is generated. The number of secondary boundaries (**B**) is chosen by the user from the following range $2 \leq \mathbf{B} \leq n$ where $\{n : n \in [3,\infty)$ and $n \in \mathbb{Z}$

$^{+}$} and {**B** : **B** $\in \mathbb{Z}^{+}$}. **B** determines how "complex" the structure society is, that is, the more

secondary boundaries there are, the more social dimension along which agents traits will be

distributed (Blau and Schwartz 1984).[3] At the outset, these secondary boundaries are exact

copies of **PB**. Third, using an iterative approach, the secondary boundaries are partially

reshuffled in order to induce a specific level of correlation between each one of them and the

primary boundary, that is, to induce correlations in the group memberships of each agent

across all boundaries. All these bivariate correlations are measured via the Pearson correlation

coefficient. When the average pair-wise correlation between all boundaries is equal to a user-

defined (target) level, the consolidation algorithm is said to have converged.[4] I denote this

user-defined (target) correlation level as Consolidation (**C**). This makes **C** the first free

parameter of interest in the model.

To model homophily, I take two steps. First, the algorithm picks one agent (ego) at

random and then makes her select one of the social boundaries that comprise the

sociodemographic (Blau) space of her society. The primary boundary and any of the secondary

boundaries have an equal probability of being selected by ego. Second, based on a user-defined

probability that I call Homophily Bias (**H**), ego creates one tie with a randomly selected alter

that has her same group membership in the boundary she just selected in the previous step.

This means that, with probability **H**, ego will create an in-group tie along the selected

boundary. Otherwise (i.e. with probability 1 – **H**), ego is instructed to create a tie with a

randomly selected out-group alter, that is, an alter that does not share ego's group membership

in the boundary under consideration. For instance, imagine a society with four boundaries

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[3] As a result, the total number of boundaries $\mathbf{B}_{total}$ (primary boundary + secondary boundaries) will always be: $\mathbf{B}_{total} = \mathbf{B} + 1$.

[4] I use a margin of error (**F**) of 0.001 to attain convergence. That means, for instance, that if **C** is set to 0.7, the algorithm will converge if the average correlation between boundaries fulfills the following inequality $0.699 \leq \mathbf{F} \leq 0.701$.

comprised of nominal categories: race, class, gender, and religion. Furthermore, assume that ego randomly selects the religious boundary as the basis of her decision-making process. Assume further that ego happens to be Muslim. Then, with probability **H**, ego would select an alter that is also Muslim, and with probability 1 – **H**, ego would select as an associate a non-Muslim alter. **H** is, therefore, the second free parameter of interest in the model. Finally, all the steps mentioned in this paragraph are repeated until a user-defined mean degree (**Z**) is reached.

When different values of **C** and **H** are combined, societies with tunable levels of segregation due to varying levels of consolidation and homophily around the primary boundary are effectively realized. Since I only model societies where **C** is ≥ 0, and given that **H** is a probability, the following is always true: $0 \leq$ **C,H** $\leq 1$, where {**C** : **C** $\epsilon$ ($R^+$ U [0])} and {**H** : **H** $\epsilon$ ($R^+$ U [0])}.

In the results section I will explicitly show how my model can indeed produce tunable levels of segregation based on different values of **C** and **H**. In order to measure the level of segregation along the primary boundary I will use two different measures: Modularity (Clauset, Newman and Moore 2004) and Moody's Gross Segregation Index – GSI – (Moody 2001).

On the one hand, modularity is a measure of community structure based on the fraction of observed in-group ties versus the expected fraction of randomly distributed ties. Based on the notation of Muff, Rao and Caflisch (2005), we have:

$$\text{Modularity} = \sum_{i=1}^{k}(e_{ii} - [a_{(i)_{end1}} a_{(i)_{end2}}]) \qquad \text{Eq. 2}$$

Where k is the number of communities, $e_{ii}$ is the fraction of ties in community i (i.e. $L_i$ / $L_{total}$) and $a_{(i)end1}$ $a_{(i)end2}$ is the predicted fraction of ties with both ends in community i (i.e. $[(L_i)_{end1} (L_i)_{end2}] / (L_{total})^2$). High modularity means that ties within communities are more likely than one would expect by chance. Modularity lies in the range [-1,1] where positive numbers

represent the fact that in-group ties exceed the number expected by chance (Li and Schuurmans 2011).

On the other hand, GSI measures the odds ratio of a tie between nodes of an in-group dyad (e.g. same-gender dyad) relative to a tie in an out-group dyad (e.g. different-gender dyad). When GSI is equal to 1, the odds of an in-group dyad equal the odds of an out-group dyad. This is a perfectly desegregated society. As GSI increases, the relative odds of an in-group tie (i.e. segregation) increases by a factor of GSI. Following Moody (2001: 692), I take the natural logarithm of GSI (i.e. ln[GSI]) so that the index ranges from $-\infty$ to $\infty$. An important property of GSI is that it is independent of the number of agents in any particular group (Moody 2001). This also means that, if two societies (e.g. two high schools) with the same GSI but with different sizes were to be combined, the resulting level of segregation after pooling both societies – as measured by Moody's GSI – would be the same (see Bojanawski and Corten 2014 for a formal analysis of GSI).

## Modeling Diffusion: Adoption of Innovations across Boundaries

In order to model diffusion, each agent has a binary variable, $A_i$, which defines if she is an adopter ($A_i = 1$) or a non-adopter ($A_i = 0$) at any given point in the simulation. In that context, I follow four steps to model diffusion. First, a seed agent (i.e. early adopter) is chosen. Four possible classes of seeds are available at this stage: popular agent (i.e. agent with highest number of ties), cultural broker (i.e. agent with the highest levels of intercultural capacity of brokerage), structural broker (i.e. agent with highest betweenness centrality[5]) and random agent (i.e. one agent chosen at random). Then, all the seed agent's immediate neighbors are

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[5] Betweenness centrality was formalized by Freeman (1977) and it is proportionate the number of geodesics (shortest paths) in the network that pass through a given agent.

also activated (i.e. $A_i = 1$). This set of early adopters (i.e. the seed plus her neighbors) is called the *seed neighborhood* (Centola 2015; Centola and Macy 2007).

Second, before the simulation of diffusions starts, all agents calculate the distance between themselves and all other alters in the society. In order to do so, I use the simple matching coefficient (SMC), a measure of similarity for nominal variables (Šulc 2014; Boriah, Chandola and Kumar 2008). This coefficient assigns a 1 to instances in which the group membership of agent i (ego) and agent j (alter) matches in the context of the $k_{th}$ boundary ($B_k$). Then, after going through all boundaries, the result is divided by the total number of boundaries. The SMC thus ranges between 0 (i.e. perfect cultural dissimilarity between ego and alter) and 1 (i.e. perfect cultural similarity between ego and alter).[6] Formally,

$$S(B_{ki}, B_{kj}) = \begin{cases} 1 \; if \; B_{ki} = B_{kj} \\ 0 \; if \; B_{ki} \neq B_{kj} \end{cases}$$

$$SMC_{ij} = \frac{\sum_{k=1}^{d} S(B_{ki}, B_{kj})}{d} \qquad \text{Eq. 3}$$

Where k represent the boundary under consideration, d is the total number of boundaries; and $B_{ki}$ and $B_{kj}$ represent the group membership of agent i and agent j in the context of the $k_{th}$ boundary, respectively. As shown below, the relative cultural similarity between j and j will determine the baseline probability of influencing each other. A wealth of social simulation work also uses a linear approach to measure social distance (Carley 1991; Axelrod 1997; Kitts 2006b; Dimaggio and Garip 2011).[7]

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[6] That is, $0 \leq SMC \leq 1$ where {SMC : SMC $\in$ (R$^+$ U[0])}

[7] Since my model intends to generate networks segregated along symbolic boundaries based on nominal attributes, and given that social actors tend to perceive these boundaries as comprised by nominal attributes (e.g. black, white, Asian in the context of the ethnoracial boundary), the "ultrametric" distance measure of Watts et al. (2002; see also Centola 2015), and the assumptions it entails, are not suitable for my purposes. Critically, the ultrametic distance measure in the context of Centola's (2015) simulation work requires a relatively large number of groups in the context of any given social dimension. Empirically, however, bright symbolic boundaries like those of gender, race, ethnicity, or sexuality are comprised by a relatively small number of categories (e.g. racial or gender identities). Indeed, Centola's (2015) main findings assume that there are 32 different categories along any given social dimension. Moreover, even though Centola (2015) mentions that his results are robust to a

The actual simulation of diffusion starts in the third step. Here, each simulated round one randomly picked non-adopter i ($A_i = 0$) will change her behavior if a randomly chosen neighbor j has already adopted the innovation ($A_j = 1$) *and* the cultural similarity between agents i (ego) and j (alter) is greater or equal than a random number $T_i$ drawn from a normal distribution with mean $T_{mean}$ and standard deviation $T_{sd}$.[8] $T_i$ is generated at the very beginning of the simulation process and acts as an individual-level decision threshold throughout the entire simulation. The higher the cultural similarity between i and j the higher the chances that it (i.e. the level of similarity) will indeed be greater than i's adoption threshold ($T_i$), and thus the more likely that i will imitate j (for a conceptually similar approach see Carley 1991; Axelrod 1997; Kitts 2006b).

This assumption is consistent with the available and extremely robust evidence showing that similar individuals do tend to imitate/influence each other (Marsden and Friedkin 1993; Christakis and Fowler 2007; Centola 2011). Also, by using threshold effects, I follow a longstanding tradition in the literature on social simulation in which diffusion dynamics are modeled in the same way (Schelling 1978; Granovetter 1978; Macy 1991; Valente 1995; Axelrod 1997; Centola, Willer, Macy 2005; DiMaggio and Garip 2011; Acemoglu, Ozdaglar and Yildiz 2011). In this body of work, the distribution of adoption thresholds has also been assumed to be normal (Granovetter 1978; Macy 1991; Valente 1995; Dimaggio and Garip 2011). Diffusion is stopped when a user-defined number of iterations (**Q**) is reached.

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minimum number of 8 categories per social dimension, it is also true that in such a scenario he assumes that there are 400 agents in each one of those 8 groups. In sum, therefore, the use of the ultrametric distance in the context of Centola's (2015) foundational work is directly related to both network size and the society's level of heterogeneity (i.e. number of groups). My analyses, on the other hand, are geared towards much smaller and denser networks, thus aiming at expanding the results previously reported in the literature (see results sections for more details).

[8] In this case, $0 \leq T_{mean}, T_{sd} \leq 1$ where $\{ T_{mean} : T_{mean} \in (R^+ \cup [0]) \}$ and $\{ T_{sd} : T_{sd} \in (R^+ \cup [0]) \}$

In terms of the outcomes under analysis, the overall proportion of adopters ($\mathbf{A_{overall}}$) is calculated at the end of the simulation. Critically, based on the seed agent's (for simplicity, "ego's") group membership in the context of the primary boundary, the proportion of ego's in-group ($\mathbf{A_{in}}$) and out-group adopters ($\mathbf{A_{out}}$) in the society at large is also calculated. Both $\mathbf{A_{in}}$ and $\mathbf{A_{out}}$ are direct measures of the ability of a given ego (i.e. a given seed agent) to spread an innovation widely. These three outcomes are measured as follows:

$$\mathbf{A_{overall}} = \frac{\sum_{i=1}^{N_{ns}} A_i}{N_{ns}} \qquad \text{eq. 4}$$

$$\mathbf{A_{in}} = \frac{\sum_{i=1}^{N_{ns}} A_i\, G_{i,seed}}{\sum_{i=1}^{N_{ns}} G_{i,seed}} \qquad \text{eq. 5}$$

$$\mathbf{A_{out}} = \frac{\sum_{i=1}^{N_{ns}} A_i\, |G_{i,seed} - 1)\,|}{\sum_{i=1}^{N_{ns}} |G_{i,seed} - 1)\,|} \qquad \text{eq. 6}$$

Where $\mathbf{N_{ns}}$ is the set of all agents that are not part of the seed neighborhood; $\mathbf{A_i} = 1$ if the ith agent adopted the innovation, and 0 otherwise; and $\mathbf{G_{i,seed}} = 1$ if the ith agent has the same group membership in the primary boundary as the seed agent, and 0 otherwise.

## Results

### Emergence of Segregation in Simulated Networks

In order to briefly explore the emergence of segregation in the context of the emergent networks, I held constant mean degree ($\mathbf{Z}=5$), population size ($\mathbf{N}=300$), number of secondary boundaries ($\mathbf{B}=9$), and the number of groups ($\mathbf{G}=5$). I then conducted computational experiments in which I systematically varied consolidation ($\mathbf{C}$) and homophily ($\mathbf{H}$). Appendices A.1.2 through A.1.6 show robustness checks that are the result of varying $\mathbf{Z}$, $\mathbf{N}$, $\mathbf{B}$, and $\mathbf{G}$.

As can be seen in Tables 1.1 and 1.2, the algorithm successfully reproduces tunable levels of segregation along the primary boundary. See, for instance, mid-level consolidation ($\mathbf{C}$ =0.5) in Table 1.1. In that context, if the level of homophily is increased from its minimum ($\mathbf{H}$=0) to its maximum ($\mathbf{H}$=1), then the overall level of segregation along the primary boundary goes from -0.256 to 0.255. This means, for instance, that even when homophily is at its maximum ($\mathbf{H}$=1), only half of the time ego ends up selecting an in-group alter as an associate precisely because of the structural influence of consolidation (for a graphical representation see the mid panel in Fig. 1.2).

Here it is important to note that Modularity can only reach a maximum of 0.5 in the presence of two modules/groups ($\mathbf{G}$=2), which is a constraint imposed to Tables 1.1 and 1.2. In other words, when $\mathbf{G} = 2$, a Modularity of 0.5 means that ties are indeed perfectly split (i.e. segregated) into two communities. This scenario is achieved when $\mathbf{C} = 1$ and $\mathbf{H} = 1$ (for a graphical representation see the right panel in Fig. 1.2). Finally, another interesting feature of my model is that random graphs emerge when $\mathbf{C} = 0$ (i.e. no average correlation between boundaries) and $\mathbf{H} = 1 / \mathbf{G}$. Indeed, as Table 1.1 shows, the average Modularity for $\mathbf{C} = 0$ and $\mathbf{H} = 0.5 = (1/\mathbf{G})$ is 0.001, a level of Modularity very close to 0 (for a graphical representation see the left panel in Fig. 1.2).

As shown in Table 1.2, substantially similar results are achieved if GSI is used to measure segregation. Infinity is a possible result in Table 1.2 because the denominator of the odds ratio of a tie between nodes of an in-group dyad relative to a tie in an out-group dyad can be 0 when there are no instances of out-group dyads ($\mathbf{C}$=1, $\mathbf{H}$=1) or when there are no instances of in-group dyads ($\mathbf{C}$=1, $\mathbf{H}$=0). Tables and Figures in Appendices A.1.2 through A.1.6 show qualitatively similar results for different values of the secondary parameters. Furthermore, Figure 1.3 shows graphic results after changing $\mathbf{G}$ (i.e. for $\mathbf{G} = 3$ and $\mathbf{G} = 4$).

Once I have shown that tunable levels of segregation along the primary boundary are produced by my algorithm, I can focus on the central topic of this study: the role of cultural brokers in the diffusion dynamics observed in segregated networks. In this context, I will proceed in the same way that I have in the section above. That is, I will systematically vary consolidation (**C**) and homophily (**H**) while holding constant the other parameters of the model (e.g. **Z**, **N**, **B**). After doing so, I will conduct robustness checks in order to show that my results do not depend on the specific parameter values I used in the baseline model.

## Diffusion of Innovations

As mentioned in the introduction, in this study I am particularly interested in analyzing the diffusion of innovations in relatively small, well-bounded, societies. In this context, the population size (**N**) of my baseline model will be 300 since that is the average size of high schools in the US according to evidence from the Add Health data set (Moody 2001). This empirical reference is important because the schools in the Add Health data set have been shown to exhibit high levels of segregation along bright symbolic boundaries like the ethnoracial boundary (Joyner and Kao 2000; Moody 2001; Goodreau et al. 2009) and, more importantly, these schools have also proven to be fertile ground to detect and study network-based diffusion dynamics (Shoham et al. 2012; Abrutyn and Mueller 2014; adams and Schaefer 2016; Kreager and Hayynie 2011; Moody 2002). Importantly, a society of 300 agents is small but not too small to be considered a *community* in which all individuals know each other; a situation that will likely reduce the role of networks on diffusion dynamics. In the social simulation literature such (close-knit) "communities" have been assumed to have an **N** of 100 (Mäs, Flache and Helbing 2010).

In terms of mean degree ($\mathbf{Z}$), I chose a value of 5 for the baseline model, which is the average number of close friends that adolescents report in the Add Health data set (Mundt and Zakletskaia 2014). Here it is important to note that, given the sizes of $\mathbf{N}$ and $\mathbf{Z}$ used in this study, my results are based on networks with densities that are larger than those typically reported in the simulation literature on network topology and diffusion dynamics (Watts 1999; Newman 2000; Watts et al. 2002; Centola 2015). Thus, the present study significantly expands this literature by studying denser and smaller networks.[9]

As mentioned at the beginning of this Chapter, the available evidence clearly shows that race is the closest to a bright symbolic boundary in the US in general, and in adolescent societies in particular (Christakis and Fowler 2007, 2013; McPherson 2001; Hallinan and Williams 1987; Joyner and Kao 2000; Moody 2001; Goodreau et al. 2009). Since race in the US is typically described and measured using 5 different ethnoracial groups, I set group membership ($\mathbf{G}$) to 5 in the baseline model. Similarly, the number of secondary boundaries ($\mathbf{B}$) I use in the baseline model is 9, for a total ($\mathbf{B_{total}}$) of 10 boundaries (i.e. 1 primary boundary plus 9 secondary boundaries).

Finally, in the baseline model I assume that adoption thresholds are randomly drawn from a normal distribution with $\mathbf{T_{mean}} = 0.5$ and $\mathbf{T_{sd}} = 0.05$. I chose these values because they represent an intuitive baseline scenario in which the expected value of the similarity between ego and alter across all boundaries has to be greater or equal than 50% in order for diffusion to be a possibility. However, as mentioned earlier, all the parameters mentioned above, including $\mathbf{T_{mean}}$ and $\mathbf{T_{sd}}$, will be varied when conducting robustness checks.

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[9] Centola (2015) reports that his results hold in large sparse networks where the density is ~0.006, at a maximum. My baseline model (where $\mathbf{N}$ = 300 and $\mathbf{Z}$ = 5), on the other hand, exhibits a density more than twice as large (~0.017).

In the context of the baseline model described above, Figure 1.4 shows overall levels of adoption after systematically varying **C** and **H** using four different ways (i.e. conditions) to select the early innovator: random, degree centrality (i.e. popular agents), betweenness centrality (i.e. structural brokers), and intercultural capacity for brokerage (i.e. cultural brokers). The results are presented using heatmaps where darker colors represent higher levels of adoption. For reference, the actual average adoption level in each sampled cell is also included in all heatmaps. The results are reported after averaging 100 independent realizations per condition.

The first finding that deserves to be highlighted in the context of Figure 1.4 is that my results reproduce the main results reported by Centola's (2015) paper on the social origins of networks and diffusion. That is, on the one hand, I find that highly consolidated populations imply relatively low levels of overall diffusion due to the existence of highly segregated groups (see the upper-right corner – i.e. where **C**≥ 9 and **H** ≥ 9 – of the heatmaps in Fig. 1.4). This finding is consistent with classic work that highlights the necessity of cross-cutting ties across segregated groups in order for diffusion to emerge (Blau and Schwartz 1984). If groups are extremely segregated, these cross-cutting ties are very few to non-existent. On the other hand, this classic literature misses the fact that when consolidation is minimal (e.g. when **C** is less than ~0.4 in Fig. 1.4), the levels of clustering (i.e. segregation) that could sustain wide diffusion dynamics are in fact eliminated too (Centola 2015).

Even though all four plots present in Figure 1.4 are qualitatively consistent with Centola's (2015) finding, clearly not all plots support that conclusion to the same extent. Indeed, the overall level of adoption when random agents are chosen as seeds (upper-left heatmap in Fig. 1.4) is much lower than the overall level of adoption when cultural brokers are chosen as seeds (lower-right heatmap in Fig. 1.4). The latter scenario is indeed more

consistent with the findings reported by Centola (2015). I argue that this is the case because cultural brokers have cross-cutting ties across the groups along which society is segregated. Therefore, where segregation is actually likely to be more conducive to sustain diffusion dynamics ($C > \sim 0.4$ and $H > \sim 0.5$), cultural brokers emerge as better prepared to bridge agents of (culturally) dissimilar backgrounds. As can be seen in Fig. 1.4, cultural brokers not only achieve higher levels of diffusion when compared to randomly chosen seeds; they also do so when compared to popular agents (upper-right heatmap) or structural brokers (lower-left heatmap).

A way to better understand these results is by explicitly mapping in-group vs. out-group-adoption. As can be seen in Figure 1.5, *in-group adoption* – here defined as adoption by agents that share the seed agent's group membership in the primary boundary – is very similar across conditions. In general, seed agents of any kind are very successful at diffusing the innovation across socially close alters in the network topologies in which social diffusion spreads widely ($C > \sim 0.4$ and $H > \sim 0.5$).

Figure 1.6 shows very different results, however. In this scenario, *out-group adoption* – here defined as adoption by agents that do not share the seed agent's group membership in the primary boundary – is very different across conditions. More precisely, Figure 1.6 (out-group adoption) shows very similar levels of variation than those reported in Figure 1.4 (overall adoption). This provides evidence that the key force behind overall adoption is related to the fact that cultural brokers are indeed more successful at spanning cultural holes in segregated societies by spreading innovations to socially *dissimilar* alters (Figure 1.6), not only to similar alters (Figure 1.5). As a way to summarize the evidence in favor of the effectiveness of cultural brokers, Figure 1.7 subtracts the levels of out-group adoption derived from all the least effective strategies (i.e. random, popular agents, structural brokers) from the results

obtained by the most effective strategy (i.e. cultural brokers). In Figure 1.7, therefore, larger

positive numbers (i.e. darker cells) are indicative of the degree to which cultural brokers are

more effective at diffusing an innovation. Figure 1.7 clearly suggests that selecting cultural

brokers as seeds has a decisive advantage over choosing seeds at random (upper-left heatmap),

based on their popularity (upper-right heatmap), or based on their betweenness centrality

(lower-left heatmap). The effectiveness of cultural brokers is clearly useful in topologies where

their cross-cutting ties are needed the most (i.e. **C** > ~0.4 and **H** > ~0.5).

Finally, I also tested the importance of intercultural brokerage, as opposed to

brokerage more generally. In order to do so I created a "null" version of brokerage (see Gould

1989). In this new measure, any node that bridges two unconnected alters *irrespectively of their*

*group membership* is considered to have capacity for brokerage. This means that null brokerage

removes the term $m_{(ik)}$ from equation 1. Results are presented in Figure 1.8 (null brokerage),

which after being compared with the results from Figure 1.7 (intercultural brokerage), show

that the latter strategy is more effective at diffusing the innovation. In a word, the results show

that it is the in-betweenness across different groups, not the general (i.e. null) capacity for

brokerage, what makes cultural brokers successful.

## Robustness Across Group size (G), Number of Boundaries (B), and Adoption Threshold ($T_{mean}$ & $T_{sd}$)

The results reported above show that agents at the interstices of bright boundaries

have a high capacity of spanning cultural holes, thus potentially having the ability to make

segregated networks more compact by bridging people located in (culturally) distant worlds.

My results also replicate key foundational findings regarding the effects of consolidation and

homophily for the diffusion of innovations. Finally, my results also extend these foundational

findings to smaller and denser networks than previously reported in the literature, thus

expanding the scope conditions of the literature on the effects of (segregated) network topologies and diffusion dynamics.

In this context, I explored the robustness of my results by increasing and/or decreasing the number of groups (i.e. $3 \leq \mathbf{G} \leq 10$), the number of total boundaries (i.e. $5 \leq \mathbf{B_{total}} \leq 15$), the mean adoption threshold (i.e. $0.4 \leq \mathbf{T_{mean}} \leq 0.7$), and the adoption standard deviation (i.e. $0.01 \leq \mathbf{T_{sd}} \leq 0.15$). Following Centola (2015) I held constant $\mathbf{N}$ (300) and $\mathbf{Z}$ (5) in order to not conflate network density effects with the structural effects of $\mathbf{C}$ and $\mathbf{H}$. My results hold after all these variations.

Take for instance the results after manipulating $\mathbf{T_{mean}}$. Figure 1.9 shows a comparison between the diffusion patterns of cultural brokers vs. structural brokers, the most effective and second most effective intervention strategies reported in Figures 1.4, 1.6, and 1.7. As can be seen in Figure 1.9, going from a relatively low ($\mathbf{T_{mean}} = 0.4$) to a relatively high ($\mathbf{T_{mean}} = 0.7$) adoption thresholds does not change the qualitative conclusions reached earlier. That is, cultural brokers are still more effective than structural brokers at spreading an innovation in the context of network topologies that happen to exhibit levels of segregation that are conducive to widespread diffusion. Figures in Appendix A.1.7 show similar evidence for the other parameters ($\mathbf{G}$, $\mathbf{B}$, $\mathbf{T_{sd}}$)

Appendix A.1.7 also incorporates robustness checks for the number of iterations ($\mathbf{Q}$) and the introduction of noise ($\mathbf{M}$). On the one hand, robustness checks show that my results remain true if the model runs for 50000 instead 10000 iterations. On the other hand, my results also remain true after incorporating different levels of behavioral noise ($0 < \mathbf{M} \leq 0.1$). Behavioral noise is the probability that ego will influence one of her (adopter) alters to become a non-adopter rather than the other way around (i.e. alter influencing ego to become an

adopter). This means that **M** can also be conceptualized as negative influence (Kitts 2006b; Dellaposta et al. 2015).

## Discussion and Conclusions

The intuition behind this study is relatively simple: liminality, or the state of being in-between two or more culturally distinct groups, is a key force behind an individuals' ability to span cultural holes in the context of segregated societies. In this context, I have also argued that people with liminal identities might be seen as skilled cultural translators that, precisely because of their hybrid identities, tend to occupy in-between positions in social structure. In turn, these positions allow them to make culturally segregated networks more compact by influencing their out-group alters at a significant rate. The results presented in this study support this basic intuition. More precisely, I have reported that the intercultural capacity for brokerage does help to identify agents with high potential for spreading an innovation in societies segregated along bright symbolic boundaries.

This Chapter complicates the ideas of liminality and brokerage by emphasizing their potential burdens (cf. Burt 2004). There is important evidence that shows that subjects with liminal identities often struggle in their daily lives precisely because of their cultural hybridity (Anzaldúa 1987; Wang and Collins 2016). Taking steps to develop a critical theory of brokerage was therefore needed in order to not portray a naïve image of liminal agents in general, and cultural brokerage in particular.

Further empirical and theoretical work must be carried out to identify the conditions under which culturally liminal individuals find themselves in structurally-advantageous positions to bridge structural holes. In this regard, the literature has very often assumed that network positions determine culture and identity. For instance, network positions in exchange systems are known to impact how third parties assign potential exchange partners to status

orderings and cognitive categories (Podolny 2001; Zuckerman 1999, 2000). However, much less is known in the opposite direction, that is, on how culture and identity determine network positions in general (Lizardo 2004), and actors' likelihood of being in structural positions that facilitate the brokering of cultural holes in particular. In this Chapter I have shown how exhibiting a liminal position across a bright symbolic boundary does put actors at a greater risk of bridging culturally segregated networks. It is yet to be determined which specific mechanisms push individuals to develop expansive cross-cutting networks, especially knowing how costly and sometimes even painful it is to span cultural holes.

I believe that one possibility in this regard might be related with the overall (group-level) distribution of cultural identities (e.g. group memberships) observed in a given society. Indeed, there is tangential evidence showing that, in the context of US high schools, Latinos are more likely to act as bridges between racial groups if they (Latinos) are a significantly large group (Goodreau et al. 2009). In that same article the authors show that whites segregate at higher rates than any other group when they are a numeric minority. This could mean, from a more general point of view, that when potential (racial) brokers feel that their cultural identity is sufficiently represented in a given society, they are more willing to put themselves "out there;" that is, to negotiate and broker cultural differences vis-à-vis the culturally (economically, politically, etc.) dominant group.

Finally, in this Chapter I developed a new algorithm to generate relatively small artificial societies with tunable levels of segregation. This is in itself a contribution to the literature on network topology and diffusion since the existing literature focuses on large and sparse networks (Centola 2015; Watts 1999; Watts et al. 2002). In this context, my results show that the structural effects of network topology on network-based diffusion dynamics can also

be found in relatively small and dense networks; thus expanding the scope conditions of previously reported findings.

# CHAPTER 2

# DIFFUSION AS THE BRIDGING OF CULTURAL HOLES: AN EMPIRICAL

# ANALYSIS

## Introduction

There is a vast literature documenting the existence of an obesity epidemic in the US adolescent population (Ogden et al. 2012; Valente et al. 2009; Salvy et al. 2012; Swallen et al. 2005). Obesity does not only affect the U.S. youth population, however. In fact, it is a disease with global prevalence (Malik, Walter and Hu 2013; Ng et al. 2014). The study of obesity is critical because it is a determinant of negative health outcomes like cardiovascular risk and cardiovascular mortality (Gunnell et al. 1998; Wilson et al. 2002), while also co-occurring with depression (Ladwig et al. 2006; Luppino et al. 2010) and stigmatization (Sutin and Terracciano 2013; Puhl and Heuer 2010; Mooney and El-Sayed 2016).

In particular, the study of obesity in adolescent networks has opened the door to a fairly recent and continuously growing literature that conceptualizes friendship as a key factor to explain health outcomes (Couzin 2009; Salvy et al. 2012; Macdonald-Wallis, Jago and Sterne 2012). This research stream was originally inspired by a series of foundational papers by Christakis and Fowler (2007, 2008) and Fowler and Christakis (2009) in which obesity, smoking, and happiness were found to spread through friendship networks of adults (for a critique see Cohen-Cole and Fletcher [2008]; for a response see Christakis and Fowler [2013]). Two key findings in this literature are that obese adolescents tend to be marginalized and that adolescent friendship networks are highly clustered by obesity status, that is, obese adolescents tend to be connected to one another (Shoham et al. 2012; de la Haye 2011b; Halliday and Kwak 2009; Valente et al. 2009).

In this context, multidisciplinary teams have acted upon the call made by the National Institutes of Health (Halloran et al. 2008; Gortmaker et al. 2011) to apply systems science methods – like network analysis and agent-based models – to understand and prevent the spread of disease in general, and of obesity in particular. Encouraging advances have indeed been made within this literature in terms of developing strategies to effectively model and/or shape health outcomes (Esptein 2009; Mabry et al. 2010; Valente 2012; Paluck, Sheperd and Aronow 2016), including weight-related behaviors (Bahr et al. 2009; Centola 2010; Shoham et al. 2012; Zhang et al. 2015a, 2015b; Mooney and El-Sayed 2016).

This literature recognizes the ability of agent-based modeling to build sound epidemiological models given that this methodology explicitly incorporates complex interdependencies among individuals, and between them and their environment (Homer and Hirsch 2006; Sterman 2006; Fenichel et al. 2011; El-Sayed et al. 2012; Mooney and El-Sayed 2016; Bruch and Atwell 2015; Epstein 2009; Burke et al. 1996). In particular, since obesity tends to be clustered, the design of effective interventions to control it must take into account how obese individuals affect – and are affected by – their social contacts; something that can be done rather naturally via agent-based modeling (Bahr et al. 2009; Zhang et al. 2015a, 2015b; Mooney and El-Sayed 2016). Moreover, social simulation methods can also increase the utility of existing empirical network data (e.g. Moody and Benton 2016; Morris et al. 2009; Schaefer, adams and Hass 2016); this is critical because network data are typically very expensive to collect and/or extend (Marsden 2011).

The usefulness of simulation methods to design interventions is especially powerful when empirically calibrated simulations are theoretically guided by a general model (Bruch and Atwell 2015), which is the case in this Chapter. Indeed, my general goal here is to test the main conclusion reached in Chapter 1. More precisely, in this Chapter I aim to provide empirical

evidence that cultural brokers – understood as individuals with a high capacity for intercultural brokerage – are highly capable of making networks more compact by bridging individuals that belong to culturally distinct (i.e. segregated) worlds.

In order to do so, I closely follow the simulation work of Shoham et al. (2012) and Zhang and colleagues (2015a, 2015b). More precisely, I first use statistical coefficients obtained from applying the stochastic actor-oriented model (SAOM) of Snijders (Snijders 1996, 2001; Snijders, van de Bunt and Steglich 2010) to data on friendship nominations and BMI. Then, I use those coefficients as inputs in an agent-based model to simulate the co-evolution of BMI and friendship nominations. These coefficients are thus used to calibrate an agent-based model aimed to reproduce how both BMI and a network of friendship nominations empirically co-evolve overtime.[10] Critically, once this empirical calibration is achieved, I create a set of interventions that mimic, to the best extent possible, the computational experiments I conducted in Chapter 1. Because the SAOM is in itself an agent-oriented statistical model, empirically calibrating an agent-based model with SAOM-estimated coefficients is a methodologically sound decision (Shoham et al. 2012; Zhang et al. 2015a, 2015b; Schaefer et. al 2013; adams and Schaefer 2016).

The analyses in this Chapter will focus on two manipulations: the selection of a class of seed innovator (**S**) (i.e. random agent, popular agent, structural broker, or cultural broker) and the effectiveness (**E**) of the intervention itself. Here the intervention is modeled as an artificial diet implemented as a reduction of BMI experienced by the seed agent, and her immediate neighbors, at baseline. The more effective the "diet" is, the more weight (i.e. BMI units) the agents in the seed neighborhood will lose at the beginning of the simulation. On the

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[10] I was originally introduced to this methodology, and helped refine it, in the context of the R01 NIH Grant HD-086259 (PIs: James Kitts and John Sirard).

one hand, I chose the four classes of seed innovators mentioned above in order to create a clear comparison between the empirically-calibrated results presented in this Chapter and the results from the agent-based model introduced in Chapter 1. On the other hand, following Zhang et al. (2015a), I chose effectiveness (**E**) as a way to model a health-related innovation (i.e. a reduction in BMI experienced by the seed innovator). Therefore, this Chapter will be devoted to document the impact of this artificial diet on aggregate-level changes in BMI exhibited by the population under analysis.

## **Methods**

I draw on SAOM parameter estimates reported by Shoham et al. (2012) and Zhang et al. (2015a) to empirically calibrate an agent-based model. These two studies use data from the National Longitudinal Study of Adolescent Health (Add Health) to model the co-evolution of friendship nomination and adolescent body size. Here I focus on data of 621 students observed at two time points in one specific high school commonly refer to in the literature as "Jefferson High" (Moody 2001). Due to its size and completeness, Jefferson High has been the focus of several network-based epidemiological and methodological papers in the past (Moody 2002; Bearman, Moody and Stovel 2004; Schaefer, Haas, and Bishop 2012; Shoham et al. 2012; Schaefer, adams, and Haas 2013; Zhang et al. 2015a; Rolls et al. 2015; Stadtfeld, Hollway and Block 2017).

Critically, one of the defining characteristics of this school is that it is 95% White (see descriptive statistics in Appendix A.2.1). By design, therefore, this leaves gender as an ideal candidate to study the emergence of cultural segregation along a bright symbolic boundary in the context of Jefferson High. Indeed, studies supporting the role of gender as a cultural trait that is key to understanding segregation in friendship nominations in general, and in Jefferson

High in particular, are legion (Thorne and Luria 1986; Leaper 1994; Goodreau, Kitts and Morris 2009; Mehta and Strough 2009; Faris and Felmlee 2011; Shoham et al. 2012; Zhang et al 2005a; Schaefer, Haas, and Bishop 2012; Schaefer, adams, and Haas 2013). To be sure, the "brightness" (Alba 2005) of the gender boundary in Jefferson High is important in this Chapter since a more direct empirical test of the theory developed in Chapter 1 relies on the existence of at least one such bright boundary.

After doing a brief description of the SAOM estimation method, I will proceed to replicate results showing that the SAOM estimated coefficients of Jefferson High reported in the literature can indeed be effectively used to simulate the emergence of the empirical distribution of BMI in this school. I will do so using my previous work with James Kitts.[11] In a word, I will show how the agent-based model reported in Zhang et al. (2015a) can reproduce the BMI distribution of Jefferson High at Wave 2 after simulating the interactions between students based on the network and demographic information contained in Wave 1 only. After conducting such empirical validation, I will proceed to report and analyze the experiments designed in the context of this Chapter. These experiments will manipulate, at baseline, the BMI of purposively targeted agents in Jefferson High. Critically, the characteristics of all agents (e.g. gender, friendship nomination ties, BMI, age, grade, etc.) will correspond to those of the actual Jefferson High students reported in Wave 1 (for a similar simulation approach based on "realistic" agents see DiMaggio and Garip 2012).

## SAOM Estimation

The SAOM is designed to perform inferential analyses of the stochastic processes governing the co-evolution of behavioral and network dynamics as if these dynamics were (theoretically) driven by actors' decisions (Snijders et al. 2010; Snijders 2001; Ripley et al. 2018).

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[11] See footnote 10.

More precisely, the model assumes that discrete unobserved (network or behavioral) opportunities for change, also known as "micro steps" (Snijders 1996; Snijders et al. 2010), happen in continuous time between empirically observed data points or waves. The first wave of data is not modeled but conditioned upon, which means that there have to be at least two waves of data in order to use the SAOM (Snijders et al. 2010). Parameters are estimated using the method of moments implemented by means of computer simulation in the RSiena software (Ripley, Boitmanis and Snijders 2017; Ripley et al. 2018).

Since the SAOM assumes that ties represent enduring states – instead of events (cf. Butts 2008) – changing throughout a series of micro steps, the evolving network is assumed to be the outcome of a continuous time Markov process (Snijders et al. 2010; Snijders 2001). In this Chapter, the network is a binary directed graph representing friendship nominations between students. The behavioral variable is students' BMI.

The SAOM further assumes that only one type of change, either network or behavioral, can happen at any given micro step (Steglich, Snijders and Pearson 2010). The network and behavioral opportunities for change happen at a speed controlled by a network rate function and a behavioral rate function, respectively. Moreover, at each micro step, only one randomly selected actor (i.e. ego) is deemed the opportunity for change (Snijders 1996; Snijders et al. 2010; Snijders 2001). In this Chapter, both rate functions are assumed to be constant across actors, which means that the change opportunity processes do not depend on actors' attributes (e.g. their in-degree).

Once the opportunity for either network or behavioral change is granted to a given actor, one of three things can happen, depending on whether it is a network change or behavioral change: a) there is a positive change (i.e. the creation of an out-going tie or a one-unit increase in the behavior variable); b) there is a negative change (i.e. the elimination of an

out-going tie or a one-unit decrease in the behavior variable); or c) there is no change. Two separate discrete (multinomial) choice functions are used to probabilistically evaluate the relative likelihood of these three mutually exclusive possibilities (Snijders et al. 2010; Steglich, Snijders and Pearson 2010). These choice functions are known as the *network objective function* (for network changes) and the *behavioral objective function* (for behavioral changes). These functions thus govern the behavioral and network processes being modeled. Once successfully estimated, the individual parameter values obtained in the context of these choice functions will characterize the role of each effect (e.g. the out-degree effect in the network objective function) in the contribution to an accurate reproduction of the network and behavioral dynamics observed in the data.

Continuing with an actor-based interpretation of the model, when given the opportunity for either network or behavioral change, the selected ego is assumed to "myopically" strive for higher values of her objective (network or behavioral) function in a stochastic fashion (Snijders 2005). This is said to be a myopic decision-making process because ego is subject to the restrictions imposed by the current state of the "world" (e.g. the state of the friendship nomination network and the distribution of BMI at a given micro step). [12] It is because of this rather natural choice-based theoretic interpretation of the SAOM that it can be in direct communication with agent-based models[13].

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[12] In the standard version of the SAOM (e.g. Snijders et al. 2010) – which is the one used in this Chapter – actors cannot coordinate to change their behavior or ties in a given micro step. Only ego is under control of what to do regarding her out-going ties. All the information she needs in order to make a decision is assumed to be available to her in the context of a given micro step. It is also assumed that, in a given micro step, ego has full information about her and all actors' attributes, as well as about the current state of the network.

[13] This does not mean that SAOM is the only inferential method for the analysis of network dynamics that is consistent with an actor-based theoretical interpretation (see, for instance, the relational even history model Butts 2008, 2017; Kitts et al. 2017).

Based on Zhang et al. (2015a) and Shoham et al. (2012), the specific network objective function used in this Chapter is determined by three distinct types of effects:

a) Structural effects (number of out-going ties, number of reciprocal ties, and number of transitive triplets)
b) Homophilous selection effects (sex, grade, age, and income similarity vis-à-vis alters); and
c) Behavior-related effects (ego's BMI; alters' BMI; similarity on BMI).

Similarly, the behavior objective function used in this Chapter is determined by three effects:

a) Linear behavior shape;
b) Quadratic behavior shape; and
c) BMI average similarity (i.e. peer influence).

The specific functional form and meaning of the effects listed above is explained in great detail in Shoham et al. (2012) and Zhang et al. (2015a). The actual estimated values of these effects are presented in Table 2.1

As a way to check the robustness of the methodology used in this Chapter, I replicated the results reported in Table 2.1. Results can be found in Appendix A.2.2 Convergence of the replicated model was very good and coefficients indeed had the same direction and similar sizes vis-à-vis those reported by Shoham et al. (2012) and Zhang et al. (2015a). These results gave me initial confidence about the robustness of the coefficients reported in Table 2.1 as tools to effectively model the co-evolution of BMI and friendship nominations in Jefferson High.

**Experimental Manipulation**

I manipulated both the seed innovator type (**S**) and the effectiveness of the artificial diet (**E**) to evaluate their impact on BMI. Closely following the experimental designed

developed in Chapter 1, there are four types of seed innovators available: popular agent (the agent with the highest in-degree), structural broker (the agent with the highest betweenness centrality), cultural broker (the agent with the highest intercultural capacity for brokerage, or IB[14]), and random agent (an agent picked at random). Again, following the experimental design used in Chapter 1, once the top agent in any of the four cases mentioned above is selected (e.g. the agent with highest in-degree if the option "popular agent" is chosen), all her immediate neighbors are also selected to be targets of the intervention, thus effectively reproducing the idea of *seed neighborhood* used in Chapter 1 (see also Centola and Macy 2007; Centola 2015).

After selecting a given seed innovator, and her immediate neighbors, all of them are subject to an intervention thought of as an artificial diet (Zhang et al 2015a). The effectiveness (**E**) of the diet is measured in the number of BMI units the selected agents (i.e. those in the seed neighborhood) will lose as a result of going through a diet. In the present Chapter, the effectiveness of the diet is an integer number between 1 and 5. After the agents in the seed neighborhood get their BMI reduced by **E** number of units, the simulation starts. The simulation is designed to reproduce a year of interactions between the students in Jefferson High. The actual number of iterations within a given simulation run is determined by the behavior and network rate functions empirically estimated from the data through the SAOM (see Table 2.1).

More precisely, the number of iterations is given by the sum of the rate parameter for network change (12.87) and the rate parameter for behavior change (4.17). In that context, a

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[14] See Chapter 1, especially equation 1. Since in chapter 1 IB was measured in the context of undirected networks, for the present Chapter I measured IB after symmetrizing the network of friendship nominations using the "strong" rule (Butts 2016, Goodreau et al. 2009). The original (directed) network was left untouched for all other analysis and simulations.

random integer is selected from a Poisson distribution with mean 17.04 (12.87 + 4.17 = 17.04). The resulting number is then multiplied by the total number of agents (n = 621). The outcome becomes the number of iterations (or "micro steps" in SAOM parlance) effectively carried out in a given simulation run. An important feature of the Poisson distribution is that it represents the probability of a given number of events (e.g. iterations) in a fixed interval of time with a constant rate that is independent of the time since the last event (Haight 1967). This property – sometimes called *memorylessness* – is both a signature of exponential distributions (of non-negative) numbers like the Poisson distribution and a key assumption of the SAOM given its continuous time Markov chain nature (Snijders 1996, 2001, 2005).

After calculating the number of iterations to be carried out in a given run, the agent-based model uses the network of friendship nominations, BMI, and non-BMI individual-level variables (e.g. gender, grade, age, in-degree) reported in Wave 1 as the initial conditions for the simulation. All the parameter values reported in Table 2.1, which control the dynamics of the simulation model, are held constant throughout the simulation. The critical point here is that agents' behaviors are indeed (stochastically) governed by the coefficients in Table 2.1. More precisely, this means that the agent-based model I use in this Chapter is specially designed to incorporate the coefficients in Table 2.1 into a customized algorithm that mimics the micro steps-based approach of the SAOM described at the beginning of this section (for technical details regarding this class of agent-based models see Zhang et al. 2015a, 2015b). In order to produce the results reported here I conducted 250 simulation runs per combination of seed innovator (**S**) and effectiveness (**E**), for a total of 20 possible combinations.

### Outcomes

First, I measured *overall overweight change* (**OW**$_{overall}$), the percent change in the number of overweight students outside the seed neighborhood after a given simulation run. A negative

number in this context represents a reduction in the percentage of overweight agents (i.e. agents with BMI ≥ 23) before and after the simulation run. So, for instance, if there were 150 overweight students outside the seed neighborhood at baseline, while there are only 50 after a simulation run finishes, then this will represent a reduction of $(\{[50 - 150]/\ 150\} * 100)$ - 66.66% in the number of overweight students in the population. For reference, if no intervention (**S**) is implemented whatsoever, after 250 simulation runs $\textbf{OW}_{\textbf{overall}}$ equals 15.26%, on average. To be sure, negative or small positive values of $\textbf{OW}_{\textbf{overall}}$ represent a successful diffusion originated in the seed innovator's behavior, that is, the successful contagion of a reduction in BMI originated in the seed innovator.

Second, I measure *out-group overweight change* ($\textbf{OW}_{\textbf{out}}$) as the percent change in the number of out-group overweight students outside the seed neighborhood after a given simulation run. For instance, if the chosen seed innovator happens to be a girl, then $\textbf{OW}_{\textbf{out}}$ would represent the percent change in the number of overweight boys outside the seed neighborhood before and after the simulation. Finally, I measure *in-group overweight change* ($\textbf{OW}_{\textbf{in}}$) as the percent change in the number of in-group overweight students outside the seed neighborhood after a given simulation run. This means that if the chosen seed innovator happens to be a girl, then $\textbf{OW}_{\textbf{in}}$ would represent the percent change in the number of girls outside the seed innovator's neighborhood. Critically, $\textbf{OW}_{\textbf{all}}$, $\textbf{OW}_{\textbf{out}}$, and $\textbf{OW}_{\textbf{in}}$ are the empirical operationalization of $\textbf{A}_{\textbf{overall}}$, $\textbf{OW}_{\textbf{out}}$, and $\textbf{OW}_{\textbf{in}}$ derived in Chapter 1, respectively (see equations 4, 5, and 6 in Chapter 1).

### **Results**

I start by validating the ability of the agent-based model to simulate the evolution of BMI in Jefferson High based on the coefficients in Table 2.1. To do so, I averaged the

estimated BMI distribution of Jefferson High after 100 (independent) runs of the agent-based model described in the Methods section. I then contrasted the simulation results with the empirical BMI distribution of Jefferson High in wave 2. Results in Figure 2.1 show that the agent-based model can indeed reproduce the BMI distribution of Jefferson High in Wave 2 with very high fidelity.

Once the ability of the agent-based model to reproduce the evolution of BMI in Jefferson High has been corroborated, the remaining of this section will focus on describing the results from the computational experiments. First, I report the results related to overall overweight change ($OW_{overall}$). To be sure, this outcome measures the percent change in the proportion of overweight agents by taking into account *all agents* outside the seed neighborhood. Figure 2.2 shows how $OW_{overall}$ varies by effectiveness ($E$) and by seed innovator type ($S$). Importantly, Figure 2.2 includes a condition labeled "Gender Broker" which represents the selection, as the seed innovator, of the agent with the highest capacity for intercultural brokerage across the gender boundary (see Equation 1 in Chapter 1 for more details). As discussed earlier, the gender boundary is an ideal candidate to operationalize the idea of a bright symbolic boundary in Jefferson High. As can be seen in Figure 2.2, no relevant change can be inferred from these initial results.

Interestingly, however, when out-group overweight change ($OW_{out}$) is brought into the equation, a relevant pattern does emerge. Here it is critical to remember that out-group (and for that matter, in-group) membership is determined by the specific symbolic boundary under analysis. In the particular case of Figure 2.3, gender is the symbolic boundary being evaluated. This means, for instance, that if the seed innovator happens to be a girl, then those in her out-group would be the boys in Jefferson High that are not part of her seed neighborhood.

In this context, Figure 2.3 shows that when cultural brokerage based on gender identities is the method used to select the seed innovator, a significant *lower* proportion of his/her out-group alters end up being overweight vis-à-vis the scenarios in which other types of seed innovators (i.e. popular agents, structural brokers, or random agents) are selected. This represents initial and important evidence in favor of the theory developed in Chapter 1 since cultural brokers along the gender boundary seem to be more effective at stopping overweightness from spreading among their out-group alters in Jefferson High.

Further evidence supporting the findings reported above is provided in Figure 2.4. In this case, two boundaries different from gender are used to evaluate the ability of cultural brokers to influence $OW_{out}$. In particular, Figure 2.4 shows how when grade or age are used to determine out-group membership, agents with a high capacity of intercultural brokerage across these two boundaries are also consistently better equipped to influence in a downward fashion the BMI of those of different age or grade than themselves (i.e. than the seed innovator).

Put simply, cultural brokers (across gender, grade, and age lines) do seem to be well-prepared to make segregated networks more compact by leading diffusion patterns across people culturally different from themselves. This is very important evidence in favor of the main hypothesis developed in Chapter 1.

The final piece of evidence relevant to this chapter is related to the effect of the seed innovators' artificial diet on the BMI of their in-group alters ($OW_{in}$). In this scenario, depicted in Figure 2.5, cultural brokers (across gender, grade, or age lines) are not as effective at stopping overweightness from spreading among their in-group alters when compared to popular agents or structural brokers.

Even though my main hypothesis only speaks to the ability cultural brokers to make segregated networks more compact by leading diffusion processes among alters *different* from themselves – an assertion supported by my theoretical model in Chapter 1 and by Figures 2.3 and 2.4 in this Chapter – more empirical research needs to be conducted to understand the implications of Figure 2.5. In particular, it is key to investigate how and why cultural brokers might be less successful at diffusing innovations within social contacts that are part of their same cultural group (e.g. same gender).

Here I speculate that it is always possible that cultural brokers' in-group alters see them as too culturally ambiguous; thus exhibiting resistance to follow their lead. Further modeling efforts should be carried out to address this possibility. If this in indeed the case, that will corroborate the theoretical framework developed in Chapter 1 in terms of the importance of conceptualizing cultural brokerage, and liminality more generally, as a social position that can be a burden; a source of anxiety, isolation, and pain precisely because of the cultural in-betweenness of liminal subjects (Wang and Collins 2016; Myers and Williamson 2001; Smith et al. 2014; Fazel, Wheeler and Danesh 2005; cf. Burt 2004; See chapter 1 for a critical view on liminality).

### Discussion and Conclusions

This Chapter demonstrates how to combine an empirically-oriented agent-based model with a general agent-based diffusion model in order to evaluate the empirical validity of the claims derived from the latter. In particular, I have shown how agent-based computational experiments derived from a formal theoretical exercise can be fruitfully translated into an empirically-calibrated agent-based model in order to provide empirical evidence supporting general theoretical claims. The connection between these two approaches was made by means of the SAOM of Snijders (1996, 2001, 2005), an actor-based statistical

framework that allows for a relatively easy transition between theory and empirics in the context of network dynamics models based on agents' behaviors.

In particular, in this Chapter I manipulated two mechanisms to understand the co-evolution of friendship nominations and BMI in a racially homogenous American high school. The first mechanism controlled the type of seed agent, that is, the agent bringing an innovative behavior to the table. I labeled this mechanism (**S**), and gave it four different possible values: popular agent, structural broker, cultural broker, and random agent. The second mechanism was the extent to which the innovation brought by the seed innovator was large or small. I labeled this mechanism (**E**) since it represents the effectiveness of an artificial diet experienced by the seed innovator. This "diet" was operationalized as a user-defined reduction in the BMI of the seed agent and her immediate neighbors.

In general, my results support the theoretical framework developed in Chapter 1 in two ways, one direct and one indirect. First, the results based on out-group overweight change (**OW$_{out}$**) show that cultural brokers are indeed the most effective at stopping the spreading of overweightness among out-group alters. In particular, three different boundaries that are known to be correlated with segregation in networks of high school students (Goodreau et al. 2009) were tested: gender, grade, and age. In all three cases, cultural brokers significantly outperformed popular agents, structural brokers, and randomly selected agents in terms of their ability to stop the spreading of overweightness among their out-group alters. This constitutes the primary and most direct source of evidence in favor of the hypothesis developed in Chapter 1, a hypothesis according to which cultural brokers are well-equipped to make segregated networks more compact by bridging cultural holes.

In terms of indirect evidence, the second main outcome under analysis, that is, in-group overweight change (**OW$_{in}$**), shows that cultural brokers are the least effective to diffuse

the innovation among their own in-group alters when compared to seed innovators chosen based on traditional network centrality measures (in-degree popularity – i.e. popular agent – and betweenness centrality – i.e. structural broker –). As mentioned in the results section, however, these results do not necessarily come as a surprise because liminal agents in general, and cultural brokers in particular, can be expected to be subject to all sorts of negative (social) punishment by their in-group alters because of their in-between (i.e. culturally ambiguous) positions along prominent symbolic boundaries. This dark side of cultural brokerage and liminality was in fact theoretically developed and documented in Chapter 1.

Future work should focus on validating the robustness of the results discussed above. In particular, one of the primary limitations of this study is that the results are derived from one school only, which casts important doubts regarding how generalizable the results are in actuality. Even though my analytical strategy was directly derived from a general model, only testing this theory in different empirical contexts will allow researchers to validate the robustness of the findings reported here.

For instance, there is solid work demonstrating how the initial prevalence of a given health-related behavioral outcome (e.g. smoking) directly affects network diffusion dynamics analyzed through agent-based models using data from American high schools (adams and Schaefer 2016). Therefore, the dynamics of health-related in-group and out-group adoption dynamics by different types of innovators discussed in this Chapter must be tested in several empirical contexts to evaluate their robustness and scope conditions. It is my hope to conduct such studies in the future.

We also know that the size of the coefficients used in the simulations reported in this Chapter (see Table 2.1) would likely vary between schools (e.g. Goodreau et al. 2009), especially knowing that the ethnoracial boundary is a prominent source of cultural segregation

among adolescents that does not exert any significant influence in Jefferson High. This is important because different coefficient sizes driving the co-evolution of networks and behavior can lead to different results. More empirical and simulation work is thus needed to explore the validity of the theoretical framework put forward in Chapter 1.

Finally, it should be mentioned that the data I used in this Chapter, namely, the Add Health data set, might not incorporate current behavioral and cultural tendencies among adolescents (e.g. the importance of online interactions). In this regard it is important to keep a critical view on the results reported in this Chapter since the adolescents in the Add Health sample lived in a significantly different cultural world when compared to boys and girls attending high school today. It should be mentioned, however, that my main purpose in this Chapter was always to illustrate an approach to connect a general agent-based diffusion model with an actor-based empirical analysis of network diffusion dynamics. In this sense, the results I presented here are, in light of the general model developed in Chapter 1, a valuable contribution to the literatures on social simulation, network dynamics, and the social determinants of health.

# CHAPTER 3

## LIMINALITY ACROSS BORDERS: NETWORK INEQUALITIES AND INTERNATIONAL MIGRATION FLOWS IN THE AMERICAS, 1960-2000

### Introduction

Over a quarter of a century ago, some of the most prominent scholars on the study of international migration in Americas noted that the evidence and theories in this literature are overwhelmingly based on bilateral migration dynamics and, especially, on the migration flow from Mexico to the US (Massey et al. 1994; see also Massey et al. 1998; Waters and Jiménez 2005; Cerrutti and Machado 2015). Massey and colleagues made several recommendations, including to study both aggregate migration flows and key sending countries beyond Mexico like the Dominican Republic, El Salvador, Jamaica, and Colombia (Massey et al. 1994: 739). Despite this call, the flow of Mexicans to the US is still more studied that any other flow in the world (Massey, Durand and Malone 2002; Smith 2005; McKenzie and Rapoport 2007; Garip 2016; Chávez 2016).

I contribute to answering the above call by studying aggregate migration flows for all countries in the Americas between 1960 and 2000. I use a novel technique to estimate migration flows between 38 countries in the Americas based on newly available global bilateral stock tables (Özden et al. 2011). By doing so, I provide an unprecedented picture of decades-long migration flows in the American continent. I analyze the history of these flows by focusing on the most important migratory subsystems in the Americas (Pellegrino 2003; Cerrutti and Parrado 2015): North America, Central America and the Caribbean, and South America. Flows that are, in fact, the aggregate-level result of liminal agents' efforts to traverse powerful symbolic boundaries of nationhood in place in the Americas.

Moving from studies of bilateral migration flows to more multilateral, and truly comparative, studies is vital to further develop migration theory (Abel and Sander 2014; Kyle and Koslowski 2011; Massey et al. 1993). Focusing on specific regions of the world is a natural step to capitalize on the advantages of multilateral research designs (Massey and Aysa-Lastra 2011; Cerrutti and Machado 2015). This is the case because studying specific regions allows for cross-national analyses that traverse several cases with shared socio-cultural features, thus providing a firm grounding for comparative analyses.

I also take advantage of the fact that international migration can be represented by networks comprised of countries (nodes) connected by migration flows (ties) in order to analyze flows beyond specific subregions in the Americas. In particular, I use Temporal Exponential Random Graph (TERG) models to characterize the structural dynamics of migration flows over time. The TERGM is a novel simulation-based modeling framework to perform longitudinal analyses of the generative processes that give rise to networks. In particular, I test predictions about the existence of strong hierarchical patterns in the data, patterns that reflect the political economy of migratory exchanges between countries. I derive these predictions from the migration literature that has highlighted the importance of chain-like flows between countries. I formalize these predictions using theories of triadic closure; thus building bridges between migration and network theories.

Finally, given that I focus on the Americas, most of the flows analyzed in this Chapter are in fact migratory movements between countries in Latin America. Indeed, it is known that Latin American migration is typically intraregional (Cohen 2010; Sporlein 2015). Here, therefore, I also contribute to the literature on migration flows within the Global South, which are severely understudied (Nawyn 2016; Malhotra, Misra and Leal 2016). Indeed, my analyses will include typically neglected countries within the Global South such as Belize, Suriname, or

Guyana (Hoefte, Bishop and Clegg 2015; Hoogbergen and Krujit 2006; Everitt 1984). In this context, my aim in this Chapter is to provide a thorough description and explanation of the evolution of migration flows in the Americas between 1960 and 2000 understood as the aggregate-level behavior of individual migrants seen as liminal agents (Menjívar 2006; Mann 2016; Huang et al. 2008).

## International Migration in the Americas: An Overview

The past and present of the American continent is inextricably entangled with the political economy of migratory movements from Europe, Africa, and Asia. Starting from the immigration flows that originated in Western and Southern Europe at the end of the 15th century, to the massive incorporation of African slaves – mainly from West Africa and Angola – between the 16th and 19th centuries, to the incorporation of Asian slaves and laborers – mainly from China and Japan – during the 19th century, many migratory waves have greatly shaped the Americas (Cohen 1995; Cohen 2010). Similarly, between the mid-19th century and the first half of the 20th century, many Latin American states partook in racialized projects to incentivize the migration of Europeans in order to whiten the ethnoracial composition of their populations (Loveman 2014; Telles 2004). Some countries, such as Brazil, Argentina, Uruguay, Venezuela or Cuba, were relatively successful in attracting European migrants to American soil (Pellegrino 1995; Loveman 2014; Telles 2004).

However, after centuries of being a pole of attraction for international migrants, in the late 1960s and 1970s Latin America became a net exporter of emigrants (Zavala and Prieto 2014; Pellegrino 1995). Durand and Massey (2010: 23) describe this as a major "turning of the [migration] tide." Massive emigration emerged, among other things, due to the increased levels of inequality and slow economic growth in Latin American (Durand and Massey 2010). Bad

economic times would become even more pressing during the years to come, especially during the so-called *lost decade* of the 1980s (Kliksberg 2001), when Latin America witnessed generalized poor economic growth, the implementation of US-sponsored neoliberal reforms, and several large-scale economic crises in countries like Mexico, Brazil, and Argentina (Martínez and Soto 2012; Portes and Roberts 2005). Increasing economic inequalities between countries in the Americas in general, are with Latin America in particular, further stimulated migration (Pellegrino 1992, 1995, 2003). Examples of these economically-driven flows are legion: Bolivian and Mexican *braceros* flowing to Argentina and the US, respectively; Bolivian and Paraguayan domestic workers going to Buenos Aires; and Haitian coffee harvesters flowing to the Dominican Republic (Cerrutti and Parrado 2015; Courtis and Pacecca 2010; Massey and Durand 2010).

Concomitantly, several Latin-American countries endured powerful dictatorships and deathly civil wars that forced people to emigrate (Durand and Massey 2010; Cerrutti and Parrado 2015). Migration from El Salvador, Nicaragua, Colombia, Chile, and Peru was indeed severely affected by political instability. Lundquist and Massey (2005) show that Nicaraguan civil war between the Sandinistas and US-sponsored Contras generated a massive in-flow of refugees to the United States. Shellman and Stewart (2007) show strong empirical associations between political violence and emigration from Haiti to the United States between 1994 and 2004. Similarly, Silva and Massey (2015) show that political violence did promote international migration of Colombians between 1986 and 2002. Political shocks (e.g. extended electoral violence) also incentivized the decision to emigrate in Peru, Nicaragua, and Mexico (Hiskey and Orces 2010).

A report from the Latin American and Caribbean Demographic Centre, CELADE, encapsulates the dramatic changes experienced in the migration dynamics in the Americas between 1960 and 2000:

> In Latin America, only considering population movements within the region and towards North America, population censuses indicate that the number of migrants grew from 1.5 million in 1960 to 11 million in 1990. This means that whereas 40 years ago Latin American migrants accounted for about 0.7% of the region's total population, in the past decade [i.e. 1990s] the proportion is likely to have reached 2.5%, having grown much faster than total population (6.6% on an annual average basis compared to 1.8%). (CELADE 2000: 11)

There is a final factor that warrants mentioning in this overview. Starting in the 1960s, several economic integration initiatives began to take place within the Americas. In 1960, Guatemala, Costa Rica, Nicaragua, Honduras, and El Salvador founded the Central American Common Market (CACM). The Latin American Free Trade Association (LAFTA) was also founded that same year.[15] The Andean Group was founded in 1969, and it was originally formed by Colombia, Chile, Ecuador, Peru, and Venezuela. The Andean Group is the direct antecessor of the Community of Andean Nations (CAN). The Caribbean Community (CARICOM) was originally founded in 1973 by Barbados, Jamaica, Guyana, and Trinidad and Tobago. The Southern Common Market (MERCOSUR) was founded in the first half of the 1990s by Brazil, Argentina, Uruguay and Paraguay. Finally, NAFTA, the free trade agreement between Mexico, Canada, and the US, was implemented in the first half of the 1990s.

All of these integration processes substantially facilitated intraregional migration in the Americas (Durand and Massey 2010). A case in point is the CAN, one of the earliest and most ambitious integration projects in Latin America (de Villegas 1977). Martínez and Stang (2006) report that in the 1990s 74 percent of all international migrants in Latin America born in one

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[15] Originally comprised by Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Paraguay, Peru, Uruguay and Venezuela.

of the five Andean countries emigrated to one of the other four Andean countries.[16] In this context, the CAN developed novel regulations like the Andean Instrument of Labor Migration, also known as Decision 116. This innovative regulation was implemented in the 1970s in order to facilitate migration of workers within the Andean region (Martínez and Stang 2006). More recently, CAN's Decision 504 allows citizens of Andean countries to travel freely within the Andean region with no visa. Regulations like these naturally facilitate migration.

In sum, it is clear that the years under analysis in this Chapter represent both an inflection point, in and a distinctive period of, the history of migration flows in the Americas. The 21st century would bring important changes in this regard. To an important extent, these new changes made migration dynamics in the continent qualitatively different. As Christopher (2002) and Mohapatra and Ratha (2010) note, some of the most important changes in this regard are related to effects of 9/11 and the economic recession the US experienced in the first decade of the 21st century. These events substantially changed migration to the US, by far the main destination country in the system. Documented and undocumented migration to the US, tourism, remittances, and even the relatively advanced negotiations of a new reform to the US migratory system, were indeed negatively affected by the situation of the US (Mitchell 2002). Similarly, Argentina, the most important destination country in Latin America, also went through a devastating economic crisis in 2001. This crisis greatly changed immigration to, and emigration from, Argentina (Bastia 2011). Given the magnitude of the changes that took place in the 21st century, the aim of the present Chapter is to describe and explain the evolution of migration flows in the Americas in the distinctive period between 1960 and 2000.

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[16] The Andean community was reduced to five members in 1974 after Chile withdrew. In 2006, Venezuela also withdrew.

**Theory and Hypotheses**

**Triadic Closure and Migratory Chains: Cyclicality and Transitivity in Migration Flows**

On the one hand, there is a relatively new literature in which aggregate-level migration flows are understood, and modeled, as social networks (Desmarais and Cranmer 2012a; Chun 2008; Ke et al. 2006). On the other hand, there is a well-established literature on the pervasiveness of triadic closure in social networks (Simmel 1922[1955]; Granovetter 1973; Rivera et al. 2010). I aim to combine these two literatures by showing how a local within-the-network (i.e. endogenous) pattern, namely, *the emergence of triadic closure in the context of migratory chains*, can provide a micro-level explanation to the hierarchical structure of the system of migratory flows in the Americas as a whole. I posit that any explanation of a system of migration flows that does not fully take into account the hierarchical nature of migratory exchanges at a local level is, at best, incomplete.

Here, I start by pointing out that a long-standing literature in social network analysis has shown that non-trivial implications arise when one shifts the analysis of social relations from dyads to triads (Simmel [1922] 1955; Cartwright and Harary 1956; Davis and Leinhardt 1972; Rawlings and Friedkin 2017). There is no a priori reason to expect that the analysis of migration flows is an exception to this rule. Indeed, when the analysis of migration dynamics is based on dyads – which is typical in the literature –, one should not be surprised to find high levels of reciprocity and (geographic) propinquity. For instance, we know that Mexicans tend to migrate to the US (Massey, Durand and Malone 2002), but that Mexico is also a top destination for US citizens (Croucher 2009a). The same goes for cases like Venezuela and Colombia (Pellegrino 2003, 1992) or Brazil and Paraguay (Rochcau 1983). However, when one

goes beyond dyads and their bilateral exchanges in order to enter the world of triads, migratory exchanges between three or more countries, what I call *migratory chains*, naturally become part of the analysis. In this context, I capitalize on the unprecedented scope of my data to analyze closure patterns in all the migratory chains observed between 1960 and 2000 in the Americas. As explained in detail below, I expect triadic closure of migratory flows to follow very strong hierarchical patterns.

To be sure, a *triad* is any set of three nodes (i.e. countries). Similarly, a *triangle* is a triad in which all nodes are connected. In this context, I first argue that migratory flows are likely to exhibit a low frequency of horizontal-like triangles, also known as cyclic triangles. Here, a *cyclic triangle* is a triangle in which migration flows exhibit a circular pattern where each one of the three countries under analysis sends a flow and receives one back (graphically, ). Similarly, following Goodreau et al. (2009), I distinguish between process and pattern by the terms *cyclicality* and *cyclic closure*, respectively. I also argue that flows are likely to exhibit a high frequency of vertical-like triangles, also known as transitive triangles. Here, a *transitive triangle* is a triangle in which one country sends flows to the other two countries and receives none from them, while one country receives flows from the other two countries and sends none to them (graphically, ). I distinguish between process and pattern by the terms *transitivity* and *transitive closure*, respectively. Critically, when there is evidence of transitivity and (anti)cyclicality occurring concomitantly, that represents strong evidence that hierarchical mechanisms at the local level underlie the emergence and evolution of a given (global) network (Kitts et al. 2017; see also Windzio 2018).

Importantly, dyadic reciprocity, propinquity (e.g. countries being in the same subregion) or homophily (e.g. countries sharing the same official language) can enhance the chances of triadic closure and vice versa (Goodreau et al. 2009). For instance, if an hypothetical

triangle with countries sharing the same official language and also located within the same subregion exists (e.g. Peru → Ecuador → Venezuela, graphically ⟋⟍), then a tie from, say, Peru to Venezuela, not only would increase the count of observed transitive triangles (graphically, ◺), but also of within-category dyads by region and by language. A correct estimation of either generative process (geographic propinquity, cultural homophily, transitivity) must therefore control for the other. In order to take into account these overlapping endogenous dependencies, as well as exogenous factors, and the configuration of the network at previous points in time, I use the TERG model.

Once properly isolated, I would interpret the hypothesized existence of triad-based hierarchical patterns – i.e. transitivity and (anti)cyclicality – observed in the context of migratory flows as indicative of the latent unequal nature of exchanges between countries, not as a mere epiphenomenon (cf. Windzio 2018). The existence of these hypothesized hierarchical patterns is in line with decades of evidence highlighting the vertical, core/semi-periphery/periphery, structure of exchanges between countries along dimensions like trade, military interventions, diplomatic relations, treaty memberships, and associations through intergovernmental organizations (Cardoso and Faletto 1974; Snyder and Kick 1979; Alderson and Beckfield 2004; Beckfield 2010). Indeed, I see the existence of hierarchically structured migratory flows as (only) one dimension of the political economy of a highly unequal global field, a political economy these migration flows help (re)produce (Friedmann 1986; Sassen 2008; Cohen 2008). Examples of the hierarchical nature of international migration flows, and of the inequalities they (re)produce, are legion: from the brain drain of top-level professionals to the emergence of "global care chains" to the existence of "global diasporas" (Ehrenreich and Hochschild 2003; Parreñas 2001; Sassen 2006, 2008; Cohen 2008).

In the following paragraphs, I attempt to provide a topology of chain-like migratory flows in the Americas using migration theory and history. These migratory chains are the empirical basis of my triadic-based hypotheses, analyses, and methods. During my exposition of these ideal types I will use cases from the three migratory subsystems at play in the Americas.

## Closure and Top-Down Migratory Chains in the Americas

As a first example of the hierarchical nature of migratory flows in the Americas I will discuss top-down movements described by the chain-like migration pattern known as *relay migration* (Durand and Massey 2010; Segal 1987; McElroy and Albuquerque 1990). Probably the best example of a relay migration pattern in the literature is Durand and Massey's (2010: 40-41) classic account of the labor migration that connects Haiti to the US:

> The process began at the upper part of the labor ladder, in the United States, and resulted from deliberate labor recruitment. After World War II, labor markets in the northeastern United States required new workers to replace aging European immigrants who had arrived earlier in the century (…) The departure of [Puerto Rican] workers to the United States from rural areas created job openings that were then filled by immigrants from the Dominican Republic, a short boat ride away, who arrived in significant numbers to cut sugar cane and harvest coffee. In this case there was no active labor recruitment because news about the availability of seasonal jobs filtered back to the neighboring island, where salaries were lower, initiating voluntary undocumented migration. In turn, rural areas of the Dominican Republic began to experience a shortage of workers owing to the departure of workers for Puerto Rico as well as the capital city and, after 1965, the United States. The shortage of workers in the coffee and sugar industries was then met by recruiting workers from Haiti, the poorest country in the Western Hemisphere, whose inhabitants viewed seasonal labor in the Dominican Republic as an economic opportunity.

I posit that the mobility of international labor migrants as described above can be understood and analyzed through a framework rooted in network theory: vacancy chains (White 1970). Given that vacancy chains have proved useful to understand the dynamics of (internal/domestic) job markets (White 1970; Chase 1981; Smith 1983; Blum, Roth and Rothblum 1997), I argue that they can be extended to understand internationally concatenated

job markets; which are the backbone of relay migration patterns (Durand and Massey 2010; McElroy and Albuquerque 1990). Critically, a key scope condition of vacancy chains is that individuals must need or want new "bigger" or "better" resource units (e.g. jobs) from time to time (Chase 1981: 135). Put simply, vacancy chains are assumed to be driven by vertical, rather than horizontal, movements. This scope condition goes in line with migration theory and evidence since we know that migration flows do tend to signal, among other things, movements of people looking to improve their – often precarious – living conditions beyond their countries of origin, which includes actively looking for better paying jobs abroad (Piore 1979; Ravenstein 1885, Arango 1985; Sassen 2008; Leal 2014).[17]

As shown in Durand and Massey's account, vacancy chains are top-down by definition since they emerge when high-type resource units (e.g. relatively high paying jobs in the US) are available (Chase 1981). The logic is simple: individuals occupying middle-type resource units (e.g. workers in the Puerto Rico – PR –) are expected to be drawn to newly available high-type resource units (e.g. jobs in the US). Once individuals that used to occupy middle-type resource units leave them to occupy high-type resource units (PR→US), individuals occupying low-type resource units (e.g. workers in the Dominican Republic – DR –) are expected to be drawn to the newly vacant middle-type resource units (DR→PR). Two triads thus emerge (triad 1: [DR→PR]; [PR→US], and triad 2: [HI→DR]; [DR→PR], graphically both triads can be represented as follows ⸫).

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[17] This does not mean that international migrants do always and permanently get better paying jobs in the destination country, or that they have perfect information before making the decision to migrate. Indeed, the lack of access to better jobs is part of the reasons behind return migration dynamics (Gmelch 1980; Leal 2014). The idea of "better" jobs is also necessarily relative, especially when comparing the point of view of native individuals and international migrants. In line with dual labor market theory (Piore 1979), better jobs for international migrants do mean, more often than not, entry-level jobs in the destination country. In the eyes of migrants, however, these jobs represent employment opportunities that will likely translate into important income gains for them and their families (Massey et al. 1993).

The vertical nature of vacancy-chain migratory flows not only explains the emergence of relay migration patterns, it also operates as a relevant force to close the triads (i.e. the explain the emergence of triangles) that constitute the structural basis of migratory chains. This means, for instance, that the two triads mentioned above are far more likely to be closed by out-flows in which individuals in low-type resource units migrate with the intention to occupy high-type resource units (i.e. DR→US in triangle 1 or HI→PR in triangle 2) than the other way around. This entails that individuals occupying low-type resource units in, say, Haiti are far more likely to be drawn to high-type resource units in Puerto Rico; thus potentially giving rise to a transitive triangle ([HI→DR]; [DR→PR]; [HI→PR], graphically ⬎), than individuals in Puerto Rico to be drawn to low-type resource units left open by emigrants from Haiti; thus giving rise to a cyclic triangle (e.g. [HI→DR]; [DR→PR]; [PR→HI], graphically ⬎). I expect these two tendencies, namely, transitivity and (anti)cyclicality, to be observed above and beyond both outside-the-network (i.e. exogenous) factors and the concurrent and previous (endogenous) configuration of the network of migratory flows.

## Closure and Bottom-UP Migratory Chains in the Americas

The top-down vacancy chains behind internationally concatenated job markets are, by no means, the only instances of chain-like migratory movements in the Americas. Indeed, many other structurally similar (i.e. triadic) patterns do not tend to originate at the core of the migratory system (e.g. new vacant positions in the US), but at its periphery. A key example of this is related to the migratory movements following political or economic crises at the periphery – crises many times caused and/or deepened by countries at the core of the system (Martínez and Soto 2012; Portes and Roberts 2005; Lunquist and Massey 2005). Take the

example of the open triangle between El Salvador – SV –, Belize – BE –, and the US ([SV➝BZ]; [BZ➝US], graphically ⠶⠂).

Here, the civil war that started in the 1970s in El Salvador forced a diversification in the flow of middle-class Salvadorians that had been migrating to Belize. More precisely, this meant that the economically-driven middle-class Salvadorian migrants that had been flowing in previous years to Belize were joined by increasingly large numbers of politically-driven peasant migrants (Asomani 1982; Everitt 1984). This in-flow of emigrants from El Salvador to Belize happened in the context of a relatively large flow of Belizeans going to the US (Everitt 1984; Stavrakis and Marshall 1978).

Over time, however, the economic and political forces behind the existence of this bottom-up migratory pattern ([SV➝BZ]; [BZ➝US], graphically ⠶⠂) became stronger. On the one hand, this resulted in a "Latinization" of Belize (Everitt 1986) as evidenced by the fact that the formerly English-speaking Belize became a country in which around 50 percent of the population spoke Spanish as their mother tongue in the year 2000 (Moreno and Otero 2006). On the other hand, the large number of Central Americas in Belize in itself became a strong push factor for Belizeans (Cunnin and Hoffmann 2013; Moberg 1997; Palacio 2001), especially black Belizeans living in South Belize (Everitt 1984; Medina 1997, Vernon 1990), to leave for the US; thus reinforcing the bottom-up character of the migratory chain between El Salvador, Belize, and the US.[18] In the words of Medina (1997: 773):

> While the threatened military invasion has not occurred, during the first decade of Belizean independence tens of thousands of Central Americans, pushed out of their own countries by poverty, repression and political violence, migrated to Belize in search of land, peace and higher wages (…) Immigration exacerbated high rates of unemployment (estimated at 20 per cent) and exerted downward pressure on wages, fuelling already high rates of Belizean migration to the US primarily by urban Creoles (Vernon 1990).

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[18] It should also be noted that El Salvador was not the only Spanish-speaking country with large out-flows directed towards Belize (see section on the Central American and Caribbean migratory subsystem below).

Going back to my theoretical argument, I posit that the triads emerging from bottom-up migratory chains are subject, by virtue of the political economy of the system, to the same underlying vertical forces that shape triadic closure in the context of the top-down migratory chains analyzed earlier. Here, therefore, my main prediction remains the same: ceteris paribus, the migratory chain [SV→BE]; [BE→US] (graphically, ⸫); is far more prone to be closed by large flows from El Salvador to the US than vice versa; thus likely giving rise to a transitive triad [SV→BE]; [BE→US]; [SV→US] (graphically, ⸫). Once more, I expect these two tendencies, namely, transitivity and (anti)cyclicality, to be observed above and beyond both outside-the-network (i.e. exogenous) factors and the concurrent and previous (endogenous) configuration of the flows.

**Closure and Mixed Migratory Chains in the Americas**

The final type of migratory chain emerges not due to changes in the upper strata of the system, where the most powerful and resourceful countries can be analytically located (i.e. the US or Canada), or due to changes in the lower strata of the system, where the most disadvantaged countries can be located (e.g. El Salvador or Haiti). In mixed chains, changes originate in the middle strata of the system. The middle strata is compromised by countries that, due to their relative political and/or economic stability, are large poles of attraction for international migrants at the subregional level. As I will show in detail in the results section, three countries are part of this middle strata in the Americas: Costa Rica, Venezuela, and Argentina.

An example of this type of migratory chain is related to the triad: Colombia (CO), Venezuela (VE), and the US. Throughout the entire period of analysis, the large flow of Colombians to Venezuela (CO→VE) is a constant. This flow is in fact one the largest in the

Americas after the flow Mexicans to the US (Pellegrino 1993, 1995, Cerrutti and Machado 2015). Similarly, between the first three decades under analysis, there was a much smaller but nonetheless constant migration of Venezuelans to Colombia. During the late 1980s and in the 1990s, however, large decreases in oil prices took place. As a result, Venezuelans started to emigrate at much higher rates that before, mostly outside the Andean region. In particular, the emigration of Venezuelans to the US increased by a factor of more than two in the 1990s (ECLAC 2006; Freitez 2011). In this context, Colombians also started to migrate to two new destinations: the Tri-State area in New York and South Florida (Guarnizo 2006). From a networks perspective, this crisis in Venezuela strengthened the transitivity of the flows between Colombia (CO), Venezuela (VE), and the US since the traditional out-flows of both Colombians to Venezuela and of Venezuelans to the US (Freitzel 2011; Mateo and Ledezma 2006) were now complemented by renovated and large out-flows of both Colombians and Venezuelans to the US ([CO→VE]; [VE→US]; [CO→US] (graphically, ).

In sum, I argue that strong hierarchical mechanisms underlie local clustering in migratory chains, and that taking this into account is necessary to fulfill the main aim of this Chapter, namely, to describe and explain the evolution of migration flows in the Americas between 1960 and 2000. On the one hand, migration theory and history show how relevant it is to think in terms of migratory chains in order to understand the highly stratified and intricate system of migratory flows that emerges from bilateral flows. On the other hand, network theory and models provide robust ways to study these migratory chains, and more specifically, to assess their hierarchical nature via concepts like triads, triangles, and triadic closure. In this context, a key strength of this study is that I am able incorporate not only key endogenous (e.g. mutuality and reciprocation) and exogenous (e.g. political violence or geography) factors into the analysis in the context of novel data, but that I also incorporate time into the analysis;

thus reducing the possibility of reporting results that do not take the temporal nature of network dynamics, and their particular timing, into account. In the following paragraphs I will formalize my theory and hypotheses.

**Formalizing the Hypotheses: Closure in International Migration Flows**

The empirical migration patterns described above using the heuristics of bottom-up, top-down, and mixed migratory chains can be formalized using network theory. Here, I will explicitly explain the hypothesized probabilistic mechanisms at place, and the statistics I will use to measure them.

*Transitive Closure*: This is a local closure pattern in which triads tend to describe the following relational pattern: [i→j]; [j→k]; [i→k] (graphically, $\stackrel{\cdot}{\triangle}$). This represents a vertical closure pattern in which node i tends to close a triad of the form [i→j]; [j→k] (graphically, $\stackrel{\cdot}{\wedge}$ ) by sending a tie to node k. This should occur above and beyond other endogenous and exogenous influences, including the previous configuration of the network. In more canonical terms, the triad [i→j]; [j→k] (graphically, $\stackrel{\cdot}{\wedge}$) is the **021C triad** in the standard triad classification of Davis and Leinhardt (1972), while the transitive triangle [i→j];  [j→k]; [i→k] (graphically, $\stackrel{\cdot}{\triangle}$) is the **030C triad** in the same classification system. Table 3.1 shows this process schematically.

*Cyclic Closure*: This is a local closure pattern in which triples tend to describe the following relational pattern: [k→j]; [j→i]; [i→k] (graphically, $\stackrel{\cdot}{\triangle}$). This represents a horizontal closure pattern in which node i tends to close a triad of the form [k→j]; [j→i] (graphically, $\stackrel{\cdot}{\wedge}$ ) by sending a tie to country k. This should occur above and beyond other endogenous and exogenous influences, including the previous configuration of the network. In more canonical terms, the triad [k→j]; [j→i]   (graphically, $\stackrel{\cdot}{\wedge}$) is the **021U triad** in the standard triad

classification of Davis and Leinhardt (1972), while the transitive triangle [k→j]; [j→i]; [i→k] (graphically, ⟁) is the **030T triad** in the same classification system. Table 3.2 shows this process schematically.

Since the combination of both transitive triadic closure and negative cyclic triadic closure is a strong signature of local hierarchy in a given social network (Kitts et al. 2017; Windzio 2018), and taking into account that the political economy of exchanges between countries tend to be highly hierarchical (Cardoso and Faletto 1974; Snyder and Kick 1979; Alderson and Beckfield 2004; Beckfield 2010; Sassen 2008; Parreñas 2001), I propose the following general hypotheses:

- H1: *Ceteris paribus, international migration flows should exhibit a positive tendency towards transitive closure.*

- H2: *Ceteris paribus, international migration flows should exhibit a negative tendency towards cyclic closure.*

It should also be noted that these hypotheses directly engage and complicate the findings of Fagiolo and Mastrorillo (2007). Using migrant stock data, these authors report that international migration networks only require dyadic covariates (e.g. propinquity or common official language) to fully account for the network structure of migration data. On the contrary, here I follow recent studies that have explicitly taken into consideration the high-order dependencies (e.g. triadic configurations) inherent to aggregate-level migration data. These recent studies have shown that higher-order dependencies at the level of triads are critical to understand international migration networks. More precisely, in the first methodological introduction to the cross-sectional ERG model for weighted networks – also known as GERG model –, Desmarais and Cranmer (2012a) used as a test case interstate migration flow data

from the US. The authors report cross-sectional evidence, based on internal migration flows, that is consistent with the two triad-based hypotheses described above.

Similarly, Windzio (2018) reports supporting evidence in favor of H2 and indirect evidence in favor of H1 using ERGM and TERG models applied to international migrant stock data. In this context, the present Chapter is the first effort to combine flow-like (i.e. not stock) data with models that explicitly account for the higher order dependencies and dynamic nature of international migration processes. Furthermore, this Chapter is also the first one to carefully derive hypotheses regarding higher-order dependencies in the context of migratory chains by explicitly combining theoretical insights from both network and migration theory and empirics. Finally, given the sample size of this study and the nature of the data, this is the first comprehensive description and explanation of contemporary migration flows in the Americas for the period under analysis.

## Data and Methods

### Migration Flow Data

I estimated four decades-long migration flows between 38 countries in the Americas between 1960 and 2000. The data were estimated using the World Bank Global Bilateral Migrant Stock Database (Özden et al. 2011). These data disaggregate the number of immigrants living in a given country of destination based on official statistics for a total of 233 countries.[19] This is the most comprehensive migrant stock data set in the world that covers the period under analysis in this Chapter (Özden et al. 2011; Malhotra, Misra and Leal 2016).

Importantly, these data allowed me to use the *flows from stocks methodology* recently developed, and empirically validated, by formal demographer Guy Abel (Abel 2010, 2013,

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[19] These data excludes refugees and those who are stateless.

2017; Abel and Sanders 2014). Using a spatial interaction model, this methodology estimates the minimum number of transitions (i.e. migration flows) that should have taken place between two consecutive migrant stock matrices in order for the row and column totals of the observed (stock) matrices to be true. The model is constrained by counts of births, deaths, and the total population of the countries under analysis. The model also takes into account the geographic distance between all pairs of countries as auxiliary information in the estimation process (for a detailed technical explanation of the model see Abel 2010, 2013, 2017). In order to use this methodology, I made use of the *fss* function included in the *migest* R package (Abel 2016).

The demographic data came from the *2017 World Population Prospects* produced by the United Nations Population Division. In particular, data on total population, total deaths, and total births were harmonized and merged with the World Bank migrant stock data. A total of 192 countries had complete information both in terms of their migrant stock data and their demographic data. Appendix A.3.1 enumerates all the countries included in the estimation process. The estimation of the migration flows also took into account the costs of migration by including the geographic distance between each pair of countries. Using geographic distance as a proxy for the costs of migration is common in the literature, and has been done both in empirical studies of global migration and of migration in the Americas (Massey and García-España 1987; Palloni et al. 2001; Massey and Aysa-Lastra 2011). Geographic distance data between the capitals of all 192 countries were obtained from the French research center CEPII (Mayer and Zignano 2011). I have already reported elsewhere that my estimates of global migration flows do replicate those reported in the work of Abel (Malhotra et al. 2016) All of the relevant code and raw data to reproduce the estimation of the global migration flows between 1960 and 2000 are available in Appendix A.3.2.

Once global migration flows were estimated, I restricted the data in order to only keep countries in the Americas. This meant that I had a total of 38 countries with complete information between 1960 and 2000. The analyses of the migration flows in the three migratory subsystems in the Americas are based on these 38 countries. Out of all the countries in the Americas, only two very small independent Caribbean islands were not included in this sample: Dominica and Saint Kitts and Nevis. Both of them had less than 70,000 inhabitants in the year 2000, which corresponds to the end of the period under analysis. The name of the 38 countries can be found in Appendix A.3.3.

I gathered information on both GDP per capita and the level of political violence of each country in order to control for major macroeconomic and political factors when conducting the statistical analyses. Unfortunately, complete data on both GDP per capita and political violence is available for 32 out of the 38 countries mentioned above. However, the six cases without complete data are small countries in the Caribbean: Antigua and Barbuda, Aruba, Grenada, Guadeloupe, Martinique, and French Guiana. Only two of them, Antigua and Barbuda and Grenada, are in fact independent countries. None of these two had a native population of more than 95,000 inhabitants in the year 2000. As a result, the statistical analysis using is based on a subsample of 32 countries. I do not expect that my statistical analyses will be significantly biased given that only four small independent island countries were excluded due to data restrictions. Finally, data on political violence was gathered from the *Major Episodes of Political Violence 1946-2015 Database* produced by the Center of Systematic Peace (Marshall and Elzinga-Marshall 2017), the same center that develops the well-known Polity IV index. Data on GDP per capita were gathered from the *Adjusted Income per Capita Index* developed by Padros de la Escosura (2015). Detailed information on these data sources can be found in Appendix A.3.2.

**Measures**

*Dependent Variables*. I aim to understand the emergence and evolution of migration flows in the Americas over four decades (1960; 1970s, 1980s, and 1990s), therefore, the (socio)matrices that record these migration flows are in fact the dependent variables under analysis. Given that these networks record estimated migration flows between countries, this poses an important methodological restriction since the TERG model has only been developed to handle binary ties (Hanneke, Fu and Xing 2010; Desmarais and Cranmer 2012a; Liefeld, Cranmer and Desmarais 2017).[20] In the ERG model literature this common restrictions is solved by means of binarizing the networks under analysis by using a thresholding or thinning rule (Faust and Skvoretz 2002; Fowler 2006; Cranmer and Desmarais 2011). A thresholding rule must be applied because when all positive ties present in a given network are automatically recorded as an existing tie, the high density of the dependent network(s) tends to produce degenerate results, that is, results where the model produces unrealistic networks in which every possible tie exists (Cranmer and Desmarais 2011; for a technical explanation of degeneracy see Snijders 2002).

In order to transform the migration flows into binary ties, I created binary networks that are less dense by only coding as a 1 (i.e. as an existing flow) all of the migration flows between a given (origin) country and its top 15 destinations countries. Because of this, my analyses effectively include the most important destination countries of each country under analysis as measured by the size of their respective out-flows. Of course, the selection of this threshold is somewhat arbitrary and other threshold values were used in sensitivity analyses. Indeed, increasing and/or decreasing the threshold by a third (+/- 5 top destination countries)

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[20] Recent efforts have been made to put forward the statistical analysis of non-binary (i.e. valued) networks under the Exponential Random Graph (ERG) model paradigm (Desmarais and Cranmer 2012a; Wilson et al. 2017), none of these tools is suited for the longitudinal analysis of valued networks.

produces qualitatively similar model estimates, while also capturing networks that contain between 40 percent and 80 percent of all observed ties.[21] As part further sensitivity analyses, I run models using a completely different estimation technique for the analysis of network dynamics, the Stochastic Actor-oriented Model (Snijders, van de Bunt and Steglich 2010), and a completely different thresholding rule that is purely based on flow size not on top destination countries (see results section for details).

*Key endogenous dependencies.* As explained earlier, in order to capture hierarchical relational patterns at the level of triads, I used the following two variables: **(1) Transitive closure** captures the number of transitive triangles in the network, that is, triples that exhibit the following relational pattern: [i→j]; [j→k]; [i→k], see Table 1 for details; **(2) Cyclic closure** measures the number of cyclic triangles in the network, that is, triplets that exhibit the following relational pattern: [i→j], [j→k], [k→i], see Table 2 for details.

*Endogenous controls.* **(3) Mutuality** captures the number of pairs of countries i and j for which the following relational pattern holds: ([i→j]; [j→i]); **(4) Reciprocation** this term captures whether a tie from country i to country j leads to a tie from country j to country i in the next time period; **(5) Dyadic stability** this is a memory term that captures the number of dyads that are stable (persistent ties and persistent non-ties) between two consecutive time periods; **(6) In-degree popularity** measures the tendency of a given country to receive flows as a function of its in-degree and it is used to control for inequalities in the distribution of in-degrees. This term is also known as attractiveness by in-degree. In the context of this Chapter, this term represents success-breeds-success dynamics in which popular countries (i.e. countries with high in-degree) tend to receive more in-flows precisely because of their high

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[21] A graphical representation of the effect of different values of the thresholding rule on the number of ties present in the networks under analysis can be found in Appendix A.3.5

popularity (i.e. high in-degree); **(7) Out-degree popularity** measures the tendency of a given country to receive in-flows as a function of its out-degree and it is used to control for inequalities in the distribution of out-degrees. This term is also known as attractiveness by out-degree. It represents the mirror image of in-degree popularity in the sense that it measures the tendency of a given country to receive more in-flows (i.e. to be popular) because of its out-degree; **(8) Absolute difference in out-degree** captures homophily based on out-degree, that is, the tendency for two countries to be connected as a function of how similar their out-degrees are. Given that, by definition, a thresholding rule based on top destination countries puts a cap on countries' out-degree (e.g. top 15 destination countries), this term is used to control for any unaccounted heterogeneity in out-degree. This is important because even if a thresholding rule based on, say, the top 15 destination countries rule is used, not all countries do send migrants to 15 countries (or more) in a given decade.

*Exogenous controls.* **(9) Same region** captures nominal attribute-based homophily based on the subregions to which any two countries belong (North America, Central America, the Caribbean, the Andean Region, and the Southern Cone), thus incorporating geographic propinquity into the analysis. The historical analysis of the migration flows conducted in the next section will show the importance of these subregions; **(10) Same (official) language** captures nominal attribute-based homophily due to language/cultural (dis)similarity in a given dyad; **(11) Income \* in-degree** captures the main effect of income per capita on in-degree. Here, I use the *Adjusted Income per Capita Index* developed by Padros de la Escosura (2015) as the data source. Since the original index was calculated for 5-year periods, the final income per capita variable of a given country was computed by averaging the beginning, end, and midpoint values of this index in a given decade (e.g. 1960, 1965, and 1970); **(12) Income \* out-degree** captures the main effect of income on out-degree based on the *Adjusted Income per Capita Index*

mentioned above; **(13) Conflict * in-degree** captures the main effect of political turmoil experienced by a given country on its in-degree. Here, I use the variable *civtot* included in the *Major Episodes of Political Violence 1946-2015 Database,* which is a count variable that aggregates yearly instances of civil violence, civil wars, ethnic violence, and ethnic wars per country. For the analyses in this Chapter, the yearly counts were aggregated by decade; **(14) Conflict * outdegree** captures the main effect of political turmoil on out-degree based on the *Major Episodes of Political Violence 1946-2015 Database* mentioned above.

## TERGM Estimation

To assess the effect of key endogenous dependencies (e.g. cyclic closure) on the temporal evolution of the migration flows in the Americas, I use TERG models with exogenous (e.g. income), endogenous (e.g. mutuality), and temporal (e.g. dyadic stability) controls. With this design I assess whether hierarchical dynamics at the triadic level can explain the structure and evolution of the network over time as predicted in hypotheses H1 and H2. All of this, above and beyond the array of controls mentioned above. The TERG model is an extension of the now well-established ERG model (Goodreau, Kitts, and Morris 2009; Cranmer and Desmarais 2011; Hunter et al. 2008), an extension specially developed to incorporate inter-temporal dependencies in a time series of observed networks (Liefield, Cranmer and Desmarais 2017). The cross-sectional probability (likelihood function) of observing network *N* under the ERG model is:

$$P(N, \boldsymbol{\theta}) = \frac{\exp\{\boldsymbol{\theta}'\mathbf{h}(N)\}}{c(\boldsymbol{\theta}')} \qquad \text{eq. 1}$$

Where, $\mathbf{h}(N)$ represents a vector of statistics computed on the network (e.g. cyclic triads), $\boldsymbol{\theta}$ represents a vector of coefficients, and the denominator is a normalizing constant representing the odds of all other networks which could be created by permuting the set of

nodes under analyses.[22] When analyzing a time series with K ∈ {0, 1, …, t-1} measurements of

network *N*, and assuming that networks occurring earlier in the time series are independent

of later outcomes, the TERG model estimates the probability of a given network, $N^t$,

conditional on the observed statistics of the lagged networks $N^{t-K}$ as follows:

$$P(N^t|N^{t-K},...,N^{t-1},\mathbf{\theta}) = \frac{\exp\{\mathbf{\theta'h}(N^t,N^{t-1},...,N^{t-K})\}}{c(\mathbf{\theta'},N^{t-K},...,N^{t-1})}$$

eq. 2

The probability of observing the networks in a given time window can be estimated

by taking the product of the time specific probabilities described in equation 2.[23] ERG models

and their temporal extension can thus explicitly model the relational dependencies inherent to

network data. This is something that conventional modeling techniques like logistic regression,

and their longitudinal extensions, simply cannot fully accommodate. A thorough

methodological treatment of TERG models is beyond the scope of this study, but the

interested reader is encouraged to consult the relevant literature (Hanneke, Fu and Xing 2010;

Desmarais and Cranmer 2012b; Liefeld, Cranmer and Desmarais 2017).

In this Chapter, TERG models are fit using the *btergm* function in the *xergm* R package

(Liefeld, Cranmer and Desmarais 2014), which uses bootstrapped pseudolikelihood inference

methods to calculate confidence intervals as described in Desmarais and Cranmer (2012b).

The terms included in the model are based on those developed in the *ergm* R package (Hunter

et al. 2008). Each time a TERG model was fit a total of 250,000 bootstrap replications were

used to estimate the confidence intervals of the coefficients being estimated. ERG models use

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[22] In other words, $c(\mathbf{\theta'}) = \sum_{all\ N^* \in \eta} \exp\{\mathbf{\theta'h}(N^*)\}$, where $\eta$ is the set of all possible permutation of *N*.

[23] For instance, the joint probability of observing the networks between time points K + 1 and T (assuming that K fully encompasses the temporal dependencies of $N^t$), is given by

$$P(N^{K+1},...,N^T|N^1,...,N^K,\mathbf{\theta}) = \prod_{t=K+1}^{T} P(N^t|N^{t-K},...,N^{t-1},\mathbf{\theta})$$

simulation-based techniques to estimate goodness-of-fit. Every time a model was estimated, goodness-of-fit was evaluated after simulating 500 networks per decade to assess how close the distribution of networks simulated under the generative model represents key features of the empirical distribution of the observed networks (Cranmer et al. 2017; Goodreau et al. 2009). Finally, predictive performance was also evaluated through ROC curves. All the data and code necessary to produce the inferential results presented in this Chapter are included in Appendix A.3.2.

## Results

### Describing Migration flows in the Americas, 1960-2000

The most prominent migration flows that took place in the Americas between 1960 and 2000 will be described in this section. Since, on average, there are close to 1,000 flows per decade recorded in my data, making the analysis tractable was a primary consideration. The first step in this direction was to split the flows based on the major migratory subregions in the Americas: Central America and the Caribbean, North America, and South America (for a similar approach see Pellegrino 2003; Cerrutti and Parrado 2015). The second step was to use the so-called *circos plot* (Zhang, Meltzer and Davis 2013).

Circos plots were developed in bioinformatics research to represent relational information between genes. Recently, circos plots have also been used to depict migration flows (Abel and Sander 2014; Malhotra, Misra and Leal 2016). The circos plots are easy to interpret: the relative size of a flow is represented by the size of a given ribbon. The direction of the flow is indicated by the existence of a white gap between a given ribbon and the outer circle segment uniquely associated with each of the countries. Whenever there is gap between a given outer circle segment and a ribbon, that indicates an in-flow. In Figure 3.1, for instance,

the largest flow in the 1970s is that connecting Haiti (HT) to the Dominican Republic (DO). Note that this ribbon does not touch Dominican Republic's outer circle segment. This means that this ribbon represent in-flows to the Dominican Republic. The largest flows also display arrows indicating direction for ease of interpretation. The information to reproduce the circos plots in this Chapter is in Appendix A.3.4.

Figures in Appendix A.3.10 show that the migration of Mexicans to the US overshadows all other flows due to its relative size. As mentioned in the introduction, however, a key objective in this Chapter is to develop a thorough description of the migration flows in the Americas beyond the US-Mexico corridor. In that context, this section is completely devoted to studying the history of these flows. By doing so, I will attain one of the two key objectives of this Chapter, namely, to produce the first continent-wide description of migration flows in the Americas for the period under analysis. The second objective, that is, explaining the structural dynamics of these flows, will be accomplished in the next session.

## The Central American and Caribbean Migratory Subsystem

As evidenced in Figure 3.1, one of the major migration flows in the context of Central America and the Caribbean is that of Nicaraguans going to Costa Rica. Figure 3.1 shows that even though this flow was small in the 1960s, it grew exponentially in the following decades, especially in the 1980s and 1990s. This conforms to the findings reported in the literature (Hiskey and Orces 2010). Nicaraguans migrated to Costa Rica during these years especially due to the political instability caused by the Nicaraguan Revolution and its spill-over effects in the neighboring El Salvador and Guatemala (Durand and Massey 2010; Fernández and Narváez 1987). The majority of these migrants were peasants that came from Nicaragua right after Somoza was deposed in 1979 (Sporlein 2015). These migrants made heavy use of the

original migration networks that economic (labor) migrants had developed in previous decades in their seasonal migration to Costa Rica (Wiley 1995).

Cubans also migrated to Costa Rica for political reasons (Villa and Martínez 2000; Fernández and Narváez 1987). A clear example of this flow is that of the Mariel migrants or *Marielitos*. This was a group of Cuban dissidents that in 1980 congregated in the Peruvian embassy in Havana in search of political asylum. After negotiations between the Costa Rican and Cuban governments, hundreds of Cubans legally departed to Costa Rica from the Mariel harbor in Cuba (Fernández and Narváez 1987). An even larger contingent of Mariel migrants would arrive later to the US (Portes, Kyle, and Eaton 1992).

According to Figure 3.1, a prominent flow existed between Haiti and the Dominican Republic while at the same time an important contingent of Dominicans migrated to Puerto Rico (see, especially, the 1960s to 1980s plots). We also know that a large number of Puerto Ricans migrated to the US throughout the same period (Massey and Sana 2003). In fact, based on my estimates, on average, more than 250,000 Puerto Ricans flowed to the US per decade between 1960 and 2000. These relay migration flows connecting Haiti and the US (Durand and Massey 2010) were highlighted as an example of a top-down migratory chain in the Theory section of this Chapter.

The literature suggests that relay migration is actually very frequent in the Caribbean (Segal 1987; McElroy and Albuquerque 1990). Indeed, another prominent example of relay migration connects Grenada, to Trinidad and Tobago, to Canada/US (Segal 1987). According to my estimates, during the 1960s the top destination of emigrants from Grenada was Trinidad and Tobago (almost 3,000 migrants). Similarly, the US and Canada were the 2nd and 8th top destination countries for emigrants from Trinidad and Tobago in the same decade. This particular relay migratory pattern is partially based on Trinidad and Tobago's ability to attract

migrants from countries like Grenada because of the existence of US military bases that were built in Trinidanian soil. These bases incentivized the local service and construction industries, where migrants from Grenada tended to be hired (Valtonen 1996).

As mentioned earlier, the existence of internationally concatenated job markets –and therefore of vacancy chains– is a key force behind top-down (relay) migration patterns in the Americas. However, the emergence of bottom-up migratory chains due to economic and/or political crises in the periphery of the system is also quite prevalent. Haitian refugees in the Dominican Republic are a case in point since they remind us that Haitians not only migrated to the Dominican Republic due to relay migration forces related to vacancy chain processes. They also emigrated due to the political instability of Haitian society (Castillo 1994).

Importantly, large migration flows are not only the by-product of political or economic instability. In several instances they create large political and economic instability. An example in this regard has to do with a set of small countries that is usually forgotten when it comes to the study of the Americas in general, and to the study of migration in the Americas in particular. Countries like Belize, Guyana, and Suriname are part of this group. First of all, even though Guyana and Suriname are geographically located in South America, culturally they are part of the wider Caribbean due to their historical and cultural positionality vis-à-vis the Caribbean (Hoefte, Bishop and Clegg 2015; Hoogbergen and Krujit 2006; Pantoja 2008). These three countries share two important characteristics: first, they are among the most ethno-racially diverse and poorer countries in the Americas. Second, neither of them were a Spanish or Portuguese colony.

These three countries have also been affected by political and demographic transformations due to the continuous in-flow of migrants. In the case of Belize, there was a continuous immigration of Central Americans during the period under analysis, especially of

Salvadorians and Guatemalans (both traditional Ketchi Mayan Indians, as well as Mopan Maya and Mestizo people) (Everitt 1984). Based on the small population size of Belize, the estimated number of Salvadorians (close to 6,000) and Guatemalans (close to 5,000) flowing to Belize was indeed quite significant in the 1990s (see Figure 3.1). These numbers are revealing since at the beginning of the 1990s the native (i.e. non-migrant) population in Belize was close to only 200,000 people. Not surprisingly, therefore, this in-flow of Spanish-speaking migrants, mostly located in Belize's countryside, encountered important levels of resistance from the local population who feared Belize was "Latinizing" (Everittt 1984). These migration flows – coupled with the emigration of black-skinned Belizeans to the US (Everitt 1984) – actually changed the ethno-racial composition of Belize. Indeed, in the year 2000, more than 106,000 Belizeans were native Spanish speakers, while the total population of the country was close to 232,000 (Moreno and Otero 2006).

Interestingly, a similar situation took place between Brazil on the one hand, and Guyana and Suriname on the other. In the 1980s and 1990s, the in-flow of Brazilians to these countries was very significant, and it has continued to grow "dramatically" since then (Hoefte, Bishop and Clegg 2015: 98). According to my estimates, for instance, more than 2,500 Brazilians flowed to Suriname only in 1990s, while the total population of the country was slightly above 470,000 in the year 2000. Many of the Brazilian migrants are gold miners, known as *garimpeiros* in Guyana and *porknockers* in Suriname (Hoogbergen and Krujit 2006). Since these migration streams from Brazil have been growing steadily, they have added complexity to an already intricate ethno-racial structure that include people of British, Dutch, Hindustani, Chinese, African, and Javanese descent. Critically, the Brazilian migrants have been gradually able to dominate the gold extraction industry, which is one of the main sectors of the economy in both Guyana and Suriname; thus, generating important political and social tensions in these

countries (Hoefte, Bishop and Clegg 2015). The cases of Belize, Guyana and Suriname suggest that when there is a sustained and relatively large in-flow of migrants to small and highly diverse countries, the host societies might actually be relatively ill-prepared to incorporate (even more) heterogeneity.

The Bahamas represents a final interesting case in the context of the migration flows in Central American and Caribbean. Indeed, since the 1950s, The Bahamas became a prominent example of migratory dynamics to inviting paradisiac islands and off-shore financial centers in the Caribbean (McElroy and Albuquerque 1988), especially attractive for US and Canada retirees (McElroy and Albuquerque 1990). Concomitantly, The Bahamas is also known to be a pole of attraction for economic migrants of neighboring islands like Jamaica, Cuba, and Haiti (Franco and Di Filippo 1999). My estimates fully support this dual migratory profile. First, in terms of North-South flows, US citizens were always among the top 10 largest foreign-born populations in the Bahamas during the period under analysis. In fact, except for one decade (1970s), US citizens were consistently among the top 5 emigrants flowing to The Bahamas. Second, in terms of South-South flows, The Bahamas emerges as a net immigration country in all four decades under analysis. On average, the number of immigrants from the Caribbean that flowed to the Bahamas between 1960 and 2000 is 16.6% larger than the number of emigrants from the Bahamas to the Caribbean and Central America.

In sum, the analysis of migration of dynamics in the Central American and Caribbean migratory subsystem has provided four important insights on migration dynamics in the Americas: (1) the existence of relay migration processes based on internationally concatenated job markets (e.g. Grenada → Trinidad and Tobago → to Canada/US); (2) the existence of politically-driven migration flows that typically make use of the social infrastructure built in previous years by seasonal (economic) migrants (e.g. Nicaragua → Costa Rica); (3) the

existence of relatively large and sustained in-flows to small, highly diverse, and poor countries (e.g. El Salvador → Belize); and (4) the existence of North-South flows directed to paradisiac Caribbean islands (e.g. US → Bahamas).

**The North American Migratory Subsystem**

In a way, the North American migratory subsystem is the simplest subsystem in the Americas since it is comprised of only three countries: Mexico, the US, and Canada. In many other ways, this subsystem could be considered the most complex because it includes the largest migration stream in the world, the in-flow of Mexicans to the US (Abel and Sanders 2014; Massey and Sana 2003). The literature is no doubt a reflection of this reality. As noted in a prominent review of this literature: "far too much of the research literature is centered in Mexico, which because of its unique relationship to the USA may be unrepresentative of broader patterns and trends." (Massey et al. 1994: 739). I will not, therefore, analyze in detail the flow of Mexicans to the US since others have analyzed in great detail (Portes and Bach 1985; Massey, Durand and Malone 2002; Garip 2016).

In general, the migration of Mexicans to the US has an early important antecedent in the *bracero* program (Calavita 1992), which was in place between 1942 and 1964. A similar program is still in place in Canada, the Seasonal Agricultural Worker Program (SWAP), which started to admit Mexican workers in 1973 (Díaz 2015). Programs like these are a feature of the North American migratory subsystem. The existence of these programs is important in its own right, but also because the networks that emerged from them have been used as key resources for future migrants. As noted before, the importance of this social infrastructure for future migration is also present in the case of early seasonal flows between Haiti and the Dominican Republic or Nicaragua and Costa Rica (Baez 1986; Wiley 1995).

On average, migration from Mexico to the US is: circular/recurrent, it had a peak around 1989, has an average length of 6 years, and it is selective of young, formally uneducated – especially peasant – men that have important access to migrant networks due to communal and/or familial ties to former migrants (Portes and Bach 1985; Massey and Aysa-Lastra 2011; Durand and Massey 2010; Massey and Sana 2005). Migration from Mexico is not purely economic, however. As Hiskey and Orces (2010) have shown, systematic electoral violence did affect individuals' decision to leave Mexico. Garip (2016) has argued about the perils of understanding the complex US-Mexico flow through the lens of the average migrant. She has shown that Mexicans that emigrated to the US since the mid-1960s onwards can be empirically classified in four clusters: (1) a group of men of rural origin that migrated in the 1960s and 1970s; (2) a group of economically advantaged young men that migrated mainly in the 1980s; (3) a group of women that migrated mainly for family reunification reasons in the 1980s and 1990s; and (4) a younger cohort of urban and formally educated people that flowed in the late 1980s and 1990s.

The other face of the US-Mexico flow, that is, the migration of US citizens to Mexico is much less studied. According to my estimates, on average, close to 100,000 US citizens flowed to Mexico per decade between 1960 and 2000, with almost 500,000 flowing in the 1990s. This made Mexico be consistently ranked among the top 3 destination countries for US emigrants in the Americas, even after including Puerto Rico as a destination country. These estimates are consistent with the existing literature on out-flows of US citizens around the globe (Bratsberg and Terrel 1996).

US migrants in Mexico have been characterized as migrants of privilege (Croucher 2009a). A symbolic indication of their privilege is that they tend not to identify themselves as immigrants, but rather as Americans (permanently) living in Mexico (Croucher 2009a).

88

Migrants of privilege, both from the US and Canada, actively seek to live comfortable lives in much less expensive societies like Mexico (Croucher 2009a, 2009b), Ecuador (Hayes 2014) or Panama (Benson 2013). These migrants tend to be relatively old, close to retirement or already retired. Croucher (2009a, 2009b) also finds that US migrants in Mexico tend to be actively involved in the politics of both the US and Mexico. Usually, their lifestyle would be difficult – if not impossible – to sustain in their home country, they are *lifestyle migrants* (Hayes 2014).

In terms of the number of Mexicans that flowed to Canada, my estimates show that, on average, close to 20,000 Mexicans migrated to Canada per decade between 1960 and 2000. The 1970s represents the peak in the number of Mexicans flowing to Canada with close to 70,000 migrants. As was already mentioned, an institutional force behind the Mexico to Canada flow is the Canadian bracero program (SWAP) that started in 1973 (Díaz 2015). These *braceros* tend to work in tobacco and fruit farms in Alberta, Manitoba, Quebec, and especially, Ontario (Basok 2003).

Migration of Mexicans to Canada between 1960 and 2000 was all but massive when compared to the migration of Mexicans to the US. This stark contrast might be at least partially explained by the different orientations of the Canadian and US migratory laws. On the one hand, since the first half of the 1960s Canadian emigration policy is based on a point system that emphasizes formal education and skills. On the other hand, during the same years the US migratory policy system started to emphasize family reunification. There is some evidence suggesting that Mexican migrants tended to migrate more to the US than to Canada due to a lack of credentials (Borjas 1993).[24]

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[24] The family reunification emphasis of the US migratory system started in 1965, while the major policy changes to the Canadian system and its emphasis on skill started in 1962 (Borjas 1993).

Besides these migratory laws, relatively lower levels of social capital in the form of preexisting social networks and greater geographic distance also act as powerful deterrents in the context of the Mexico-Canada flow (Antecol et al. 2003). In fact, taking Latin America as a whole, the literature shows that previous to the 1970s, migration of Latin Americans to Canada was negligible due to lack of important economic and political connections and geographic distance (Bernhard, Landolt and Goldring 2009). Existing data for the period 1981-2000 do show that there was no Latin American country among the top 10 source countries that comprise Canada's immigrant population (Hou 2007).

The last migration flow that comprises the North American migratory subsystem is the North-North migration flow at the US-Canadian border. The literature explicitly suggests that information on this flow is relatively scant (Konrad and Nicol 2011; Ramirez 2001). Based on my estimates, between 1960 and 2000, over 160,000 Canadians migrated to the US per decade, while close to 90,000 US migrants went to Canada. It should be noted that the US-Canadian border represents an important and active boundary since most of the Canadian population lives within 100 miles of the border (Ramirez 2001). Not surprisingly, Anglo-Canadians have historically been better able to incorporate into American society than French-Canadians, although there is evidence of the role of French-Canadians as part of the development of the industrial sector in New England (Ramirez 2001).

An interesting migration phenomenon that brings together Canada and the US – and more recently Mexico – is seasonal (winter) migration (Marshall and Longino 1988; McHigh and Mings 1994), also known as snowbird migration (Coates, Morrison and Healy 2002). This is a temporary migration stream originated in Canada, and in the north of the US to a lesser extent, directed towards the US Sun Belt –and more recently to Mexico. In the case of Canadians flowing to the US, Coates et al. (2002) report that by the end of the 1990s this flow

was comprised of about 300,000 Canadian migrants that stayed in the US Sun Belt somewhere between 21 and 90 days during winter. Like the lifestyle migrants mentioned earlier, snowbird migrants tend to be relatively old and politically active (Coates, Healy and Morrison 2002; Marshall and Longino 1988; McHigh and Mings 1994). Snowbird migration is, therefore, a distinctive feature of the North American migration subsystem that binds together, for a relatively short period of time during a given year, the North American triad.

The analysis of migration dynamics in the North American migratory subsystem has provided three particular insights on migration dynamics in the Americas: (1) the importance of early institutional North-South temporary work agreements to propel migration flows later in time (e.g. the *bracero* and SWAP programs); (2) the increasing numbers of both temporary (i.e. snowbird migrants) and permanent (i.e. migrants of privilege) lifestyle migrants in North-North and North-South flows and; (3) the significance of migratory laws in order to partially understand the strength and demographic composition of South-North flows (i.e. the effects of the skill-based point system in Canada vs. the reunification-based system in the US).

**The South American Migratory Subsystem**

Previous research has shown that countries in South America comprise a distinctive migratory subsystem (Pellegrino 1995; Parrado and Cerrutti 2015). Within this large subsystem, three main types of flows can be identified: those between Andean countries, those between Andean Countries and countries in the Southern Cone, and those between countries in the Southern Cone. I start by analyzing key Andean flows.

The Andean region is comprised of five countries: Colombia, Peru, Ecuador, Bolivia, and Venezuela. From Figure 3.2 it is clear that Venezuela was, by far, the main destination country in the Andean region. This is clearly supported by the literature (Villa and Martínez 2000; Cerruti and Parrado 2015; OIM 2012; Rochcau 1983). Figure 3.2 also shows that the

largest flow in the Andean region is that of Colombians going to Venezuela. Based on my estimates, between 1960 and 2000, more than 90 percent of the 705,000 Colombians that migrated to another country in Latin America went to Venezuela. A similar estimate is reported elsewhere (Martínez and Stang 2006). The peak of this flow was in the 1970s, with close to 300,000 Colombians migrating to Venezuelan soil. Colombians in Venezuela tended to work in the construction and service industries (e.g. restaurants, hotels) and as cotton harvesters at the borders of the two countries (Escobar 1991).

A significant number of Colombians in Venezuela, especially those migrating in the 1970s, also held managerial positions (OIM 2012; Pellegrino 1995). The large flow of Colombians to Venezuela in the 1970s was not unique, however. My estimates show that, with no exception, all countries in the Andean region sent more migrants to Venezuela in the 1970s than in any other decade. This is also supported by the literature (Pellegrino 1995, 2003; Cerruti and Parrado 2015; OIM 2012). These in-flows were not solely composed of economic migrants. A significant number of political migrants from countries like Colombia, Uruguay, Chile or Argentina also flowed to Venezuela in the 1970s (Cerrutti and Parrado 2015; Silva and Massey 2015).

The migration of Colombians to Ecuador is also significant and constant in the Andean region. This flow is in fact the second largest in the Andes (OIM 2012; Escobar 1991; Cerrutti and Parrado 2015; Martinez and Stang 2006). The literature reports that during the 1960s, migration of Colombians to Ecuador was especially active at the Pacific border between these two countries (Escobar 1991; Mejía 2012). Most of these border migrants worked in the logging and rubber extraction industries (Eguiguren 2017). External economic factors like the very low oil prices reduced this flow in the 1980s (Mejía 2012; Pellegrino 1992). These fluctuations are captured in my data. My estimates show that the peak of the flow of

Colombians to Ecuador was in the 1970s (close to 16,000 migrants), while the lowest point of the flow was in the 1980s (close to 7,000 migrants). As mentioned in the Theory section in the context of my discussion of mixed migratory chains, similar fluctuations due to the crisis in oil prices are also observed in the flow of Colombians to Venezuela. During the 1990s, new push factors were positively affecting the emigration of Colombians to neighboring Andean countries. The increasing brutality of the Colombian internal conflict was prominent in that regard (Silva and Massey 2015; Mejía 2012).

In the case of Peru as an emigration country, previous to the 1980s migration to Argentina was relatively small, mostly composed of male university students (Pacecca 2000b; Hiskey and Orces 2010). This flow significantly changed during the 1980s and 1990s when Argentina became the largest destination country for Peruvians in the Americas. During the 1990s the Argentinian peso was pegged to the US dollar in an attempt to reduce hyperinflation. This fixed exchange rate incentivized labor migration to Argentina because it meant that migrants would be effectively paid in dollars (Cerrutti 2005). In that context, many Peruvian, Bolivian, and Paraguayan migrants – most of them women – migrated to Argentina, especially to cities like Buenos Aires, Mendoza, and Rosario (Cerrutti 2005; Bastia 2005, 2007; Sassone 1989). These flows exemplify both the emergence of care chains within the global South and of gendered migration flows in the region (Bastia 2009; Cerrutti and Parrado 2015, Cerrutti 2005). Fujimori's self-coup in 1992 also impacted emigration of Peruvians (Altamirano 1992). In particular, there is indeed evidence that Fujimori's regime made Peruvian women more likely to migrate than men (Hiskey and Orces 2010). The infamous forced sterilization of more than 270,000 indigenous Peruvian women by Fujimori's regime in the 1990s symbolizes the struggles of Peruvian women in these years (Ballón 2014).

In the case of Bolivian emigrants, the literature reports that Argentina and Brazil were major destinations (Ledo 2010). This is supported by my estimates since Argentina and Brazil emerge, respectively, as the first and third most common destination countries for Bolivians in each of the decades under analysis. The second most common destination of Bolivians was the US. On average, based on my estimates, close to 50,000 Bolivians flowed to Argentina per decade between 1960 and 2000. The literature reports that during the 1980s and onwards Bolivians became the largest foreign-born group in Argentina (OIM 2012). Bolivians in Argentina are reported to predominantly work as agricultural and construction workers, miners, domestic workers, and in the garment industry (Bastia 2007; Courtis and Pacecca 2010). Although Bolivian migration to Argentina is essentially economic and circulatory (Bastia 2007; Escobar 1991), political turmoil around the coup of Banzer in 1971 also incentivized emigration to Argentina (Cerruti and Parrado 2015). The flow of Peruvians and Bolivians to Argentina represent the major migratory movements from the Andean region to the Southern Cone.

As shown in Figure 3.2, the most prominent flows within Southern Cone proper are comprised of both Uruguayans and Paraguayans going to Argentina. This is supported by the literature (Franco and Di Filippo 1999; Sporlein 2015; Gómez and Bologna 2013). Based on my estimates, on average, about 68,000 Paraguayans flowed to Argentina per decade between 1960 and 2000. The peak of this flow was in the 1990s, when more than 89,000 Paraguayans migrated to Argentina. In general, years of education, lack of employment, and social ties to siblings or a wife with migration experience, have been shown to increase Paraguayan's probability to migrate to Argentina (Cerrutti and Parrado 2003). The sustained migration of Paraguayans to Argentina is also associated with Stroessner's 35-year-long (1954-1989) dictatorship (Cerrutti and Parrado 2015). Concomitantly, macroeconomic factors like

increased inflation and the deterioration of employment opportunities in Argentina, especially during the 1980s, predicted Paraguayans return migration from Argentina (Parrado and Cerrutti 2003). The construction of hydroelectric power plants in Paraguay during the 1970s and 1980s also incentivized return migration from Argentina (Villa and Martínez 2000). My estimates do show that the 1980s is the decade with the lowest number of Paraguayans (close to 24,000) flowing to Argentina.

Given that Paraguayan, Peruvian, and Bolivian flows that took place during the late 1980s and 1990s were mainly directed to large cities like in Argentina this created "alarmist attitudes" with regards to Latin American migrants in Argentina (Sassone 1989). In that context, in 1987 Argentinean President Alfonsín sanctioned a decree in which (indirect) discrimination was instituted against migrants from countries like Bolivia, Peru, and Paraguay (Bastia and vom Hau 2014). This represented a significant regulatory change since in previous decades flows to Argentina from neighboring countries were highly unregulated (Parrado and Cerrutti 2003).

The flow of Paraguayans to Brazil represents another prominent migratory corridor in the Southern Cone (OIM 2012; Cerruti and Parrado 2015). These migrants tend to be agricultural workers settled in rural areas, especially in the Brazilian states of Paraná and Mato Grosso (Souchaud 2010; Patarra and Baeninger 2004). Interestingly, the migration between Brazil and Paraguay is highly bidirectional. Rochcau (1983) notes that Paraguayans flowing to Brazil in search of jobs, and that Brazilians emigrating to Paraguay in search of land, was an exchange initially stimulated by the construction of the Friendship Bridge in 1965 over the Paraná River. Since then Brazilian peasants have had an important presence in eastern Paraguay (Pellegrino 2003; Póvoa and Sprandel 2010). Brazilians are indeed the largest foreign-born population in Paraguay, and their economic activities have diversified over time to

encompass construction work, the service industry, and commerce (Souchaud 2010). Based on my estimates, Paraguay was the top destination in Latin America for Brazilian migrants in all decades under analysis, except in the 1990s. Similarly, Brazil was always the second most popular destination in Latin America for Paraguayans. These estimates conform to evidence reported in the literature (Loreley 2005). Latin American migration was never the main source of immigrants in Brazil, however (Klein 1995). This is the result of efforts from the Brazilian state to attract qualified migrants from other latitudes (Pellegrino 1992) and of the strength of urban-rural flows within Brazil that made this country less dependent on foreign labor (Pellegrino 2003).

Finally, Chile is an interesting because it had a very stark transition in its migratory profile going from being a net emigration country between the 1960s and 1980s (Bernhard et al. 2009) to becoming a net immigration country in the 1990s (Martínez and Stang 2006; Stefoni 2010). My data do reflect these changes. Based on my estimates, more than 41,000 Chileans emigrated to other countries in the Americas in the 1990s, while more than 71,500 immigrated to Chile from the Americas. In contrast, in the 1980s, close to 83,000 Chileans emigrated to other countries in the Americas, while close to 31,000 people from the Americas immigrated to Chile. The same net emigration pattern is present in my estimates for the 1970s and 1960s. During the years of net emigration, Chile had very important flows directed towards Argentina – most of these migrants were men (Villa and Martínez 2000) –, and to a lesser extent to Brazil and Venezuela. Most of these flows were incentivized by Pinochet's dictatorship (1973-1991) (Cerrutti and Parrado 2015; OIM 2012). During the 1990s, Chile's return to democracy and its remarkable macroeconomic performance, were associated with return migration of Chileans, as well as with increased migration flows from neighboring countries like Peru (Villa and Martínez 2000; Pellegrini 2003; OIM 2012; Franco and Di

Filippo 1999). The migration of Peruvians to Chile during the 1990s was mainly directed towards Santiago and was also mainly composed of women (Stefoni 2010).

To summarize, the analysis of migration dynamics in the South American migratory subsystem has provided three particular insights on migration dynamics in the Americas: (1) the importance of external shocks like abrupt changes in oil prices to understand migration flows in the Andean region and South America (e.g. flows to Venezuela in the 1970s); (2) the relevance of care work to understand South-South migration dynamics in general, and the feminization of migration flows to large cities in the Southern Cone in particular (e.g. Peruvians going to Argentina); (3) the critical importance of transitions in and out democracy to understand emigration on the one hand, and return migration on the other (e.g. Chileans going to, and coming from, Argentina).

Once the most prominent migratory corridors in the Americas have been depicted and described, the final part of this Chapter is devoted to explain the emergence and evolution of the migratory system that emerges out of these very same flows. In order to do so, I will be relaying on techniques that allow me to capture key dynamics of migratory chains by focusing on their subjacent network structure.

**Explaining the Structure of International Migration Flows in the Americas, 1960-2000**

Table 3.3 provides descriptive statistics of the four networks of decades-long migration flows under analysis. The networks are relatively dense with an average density of 0.449, with no observed isolates. Mean in-degree is close to 14 incoming ties per country, on average. It should be noted, however, that the standard deviation of the in-degree distributions of these networks is relatively large. This is associated with the existence of long tails, which signal the existence of popular nodes or hubs, like the US, that tend to get a much larger number of in-flows than the average country. To see a graphic representation of the in-degree

distribution of each network, see Appendix A.3.6. The dyad census in Table 3.3 shows that the number of mutual dyads ([i→j]; [j→i]) is always smaller than both the number of null dyads ([i no tie j]; [j no tie i]) and of asymmetric dyads ([i→j]; [j no tie i]).

In terms of the triadic structure of these networks, which is the backbone of migratory chain, Table 3.3 shows that in the observed networks there are always a very small number of cyclic triangles ([k→j]; [j→i]; [i→k], graphically ⟁) when compared to the number of transitive triangles ([j→k]; [i→j]; [i→k], graphically ⟁). For instance, in the 1980s there were only 7 cyclic triads while there were 345 transitive triads. The ratio of triangles to triads is also very different. On the one hand, in the case of cyclic triads, the ratio of cyclic triangles (⟁) to the number of 021C triads (⟁) is 0.051. On the other hand, in the case of transitive triads, the ratio of closed triangles (⟁) to the number of 021U triads (⟁) is 0.62. The difference between these two ratios is very large since the ratio of transitive triangles to 021U triads is more than 12 times that of cyclic triangles to 021C triads. This conforms to my hypotheses since the data do suggest the existence of a positive tendency towards transitive closure and a negative tendency towards cyclic closure in the context of the migratory chains observed in the Americas.

Note that it is entirely possible that the counts of triads and triangles reported above are the product of chance, conditional on other structural features of the networks. Put differently, these observed counts might be typical of networks that happen to share similar structural features (e.g. number of ties, number of mutual dyads etc.) to the ones observed in the empirical networks.

As a first step to rule out that possibility, Table 3.3 reports counts of transitive and cyclic triangles, as well as of the relevant triads (i.e. 021C and 021U), for random simulated networks that are structurally similar to my observed networks. More specifically, for each of

the four observed networks, I simulated 500 random networks that have the same number of

nodes, and ties, and also have exactly the same proportion of null, symmetric, and asymmetric

dyads as the empirical networks. Results show that in 13 out of 16 cases, the mean number of

simulated configurations (e.g. the mean number of *simulated* cyclic triangles in the 1980s equals

84.5) is more than three standard deviations apart from the empirical count of the same

configuration (e.g. the *observed* number of cyclic triangles in the 1980s is 7). This represents

further evidence in favor of my hypotheses suggesting that there is indeed a systematic – and

highly hierarchical – process shaping closure in the migratory chains observed in the Americas.

Here I provide a final piece of descriptive evidence in favor of my hypothesis. As

mentioned in the theory section, exchanges – including migratory exchanges – between

countries in the Americas can be expected to be highly hierarchical and unequal. Furthermore,

from an analytic point, I suggested the existence of three stratum in which the countries in the

system of international migration flows can be located. Countries in the upper strata are top

players at the system-level, in the case at hand, the US and Canada. These are the countries

that have the most resources and stability, thus making them highly desirable destinations. In

that context, Table 3.4 shows how many times the US and Canada are part of migratory chains

with horizontal-like exchange patterns, that is, the number of times these two countries are in

the cyclic triangles observed in the data. The answer is clear: the US and Canada are nowhere

to be found in this kind of equal exchange situations. However, these two countries are part

of more than 26 percent of all transitive triangles, that is, of the migratory chains that are

hierarchically structured. The descriptive evidence does suggest, once more, the existence of

a highly hierarchical system where a clear pecking order between countries exists.

Table 3.5 displays results of TERG models estimating the emergence and evolution of

migration flows in the Americas between 1960 and 2000. These models go beyond the

descriptive results in Table 3.3 by means of including other endogenous dependencies (e.g. in-degree popularity), as well as exogenous factors (e.g. level of political conflict) and the configuration of the network at previous time points (e.g. dyadic stability). The evidence from the TERG model strongly conforms to my hypotheses: local patterns of relational deference at the level of triads play a key role in the generative process behind the evolution of migration flows in the Americas; thus evidencing the hierarchical nature of the Americas migratory system. These effects are not a mere nuance; they are empirically robust and also make sense theoretically once migratory chains are laid out in the context of such a highly stratified system.

The results in Table 3.5 report that the coefficient for cyclic triangles is of -0.154, which means that an additional tie i→k that closes a triad of the form [k→j];[j→i] (graphically, ⟨⟩) *decreases* the odds of the existence of a flow from i to k by [100 * (exp(0.154) − 1)] ≈ 17 % on average, conditional on the rest of the network. On the other hand, the coefficient for transitive triangles is of 0.140, which means that an additional tie i→k that closes a triad of the form [i→j]; [j→k] (graphically, ⟨⟩) *increases* the odds of the existence of a flow from i to k by ≈ 15 % on average, conditional on the rest of the network. The results hold after incorporating exogenous covariates previously used in the literature like income, political violence, language and geographic distance (Fagiolo and Mastrorillo 2007; Özden et al. 2011). More importantly, these results also hold above and beyond both contemporaneous dependence processes like mutuality (e.g. the tendency of flows j→i and i→j to co-occur) and inter-temporal dependence processes like dyadic stability (e.g. the tendency of a flow from j→i to remain in time). All of this supports the hypotheses developed in the Theory section.

In terms of the goodness-of-fit of the model, Figure 3.3 show that the estimated model reported in Table 3.5 fits the data very well. Except for the plot in the bottom right corner, the different plots in Figure 3.3 shows box plots representing the distribution of six network

statistics computed on 500 simulated networks per decade. These 500 networks per decade are all simulated under the generative model in Table 3.5 and are compared to the empirical distribution of the same six statistics, as represented by the solid lines. All these plots show evidence of very good fit. The bottom right plot in Figure 3.3 shows ROC curves estimated for each one of the fitted networks in order to further assess the accuracy of the TERG model. All curves have a score > 0.8, which is conventionally considered as good fit. It should be noted that the network corresponding to the 1960s is excluded from all plots in Figure 3.3 since the first network in the series of observed networks (i.e. the 1960s) is actually not modeled, but taken as the initial source of information to fit subsequent networks (Liefeld, Cranmer and Desmarais 2016) Finally, Appendix A.3.8 shows that model in Table 3.5 is not degenerate.

Importantly, Table 3.6 shows how the two key coefficients under analysis (i.e. transitive triangles and cyclic triangles) vary based on different threshold values. The coefficients in Table 3.6 are estimated after controlling for all relevant covariates included in Table 3.5. For ease of expositions, however, I only present the coefficients relevant for my hypotheses. The full TERG models based on the different thresholding rules can be found in Appendix A.3.7.

Table 3.6, therefore, provides further support for my hypotheses since it is clear that by including fewer flows (e.g. top 10 destination countries vs. top 15 destination countries), that is, by analyzing only the largest flows in the system, the strength of transitivity and (anti)cyclicality is amplified. On the other hand, by including more flows (e.g. top 20 destinations vs. top 15 destination countries), the strength of transitivity and (anti)cyclicality is reduced. In a word, the results show that as one focuses on the most prominent migratory corridors in the Americas, the hierarchical nature of the system is more palpable. Qualitatively

similar results are found using a completely different thresholding rule, based on actual flow size, and a completely different inferential technique, the Stochastic Actor-oriented Model (see Appendix A.3.9 for these results and their rationale).

## Conclusions

Throughout this Chapter I have taken several critical steps to push forward the field of international migration. First, I have estimated migration flows in the Americas during the distinctive period between 1690 and 2000. By doing so, I have provided an unprecedented picture of decades-long migration flows in the Americas. Relatedly, by capitalizing on the breadth and scope of my data, I have described in detail the main migratory corridors in the Americas, thus providing a unified description of the literature on migration flows in the Americas, a literature that is highly scattered due to the its emphasis on bilateral case studies. Second, by capitalizing on the relational nature of my data, I have provided a network-based theory of migratory chains based on the existence of three analytically different stratum: an upper strata (US and Canada); a middle strata (Costa Rica, Venezuela, and Argentina); and a lower strata (all other countries). Moreover, by analyzing the history of flows with the aid of both circos plots and network-based descriptive statistics, I have shown that the concept of migratory chain allows for a description of the intricate and highly stratified system of migration flows in the Americas. Third, I have tested hypotheses in order to show that the stratified/hierarchical nature of system can be traced down to key processes taking place at the local level, namely, to the transitivity and (anti)cyclicity of the migratory chains. Finally, I have also shown that these local tendencies are very stable blueprints of the system, thus making them necessary to explain the emergence and evolution of the overall system over time.

Future work should address important questions that remain answered. First, several questions related to closure of migratory chains need deeper theorization and analysis. For instance, are top-down migratory chains more likely to be exhibit stronger tendencies towards transitivity and (anti)cyclicity when compared to mixed migratory chains and/or bottom-up migratory chains. Second, are the results provided in this Chapter robust to different time periods, different geographies, or to a gender-based analysis? Testing the theory put forward in this Chapter in a different continental system (e.g. Asia or Africa), at a global scale, or by analyzing gender-disaggregated flows, would be critical in this regard. Third, from a methodological point of view, can we assess what are the advantages of using a network-based approach as a predictive tool to model flows-as-networks when compared to more traditional approaches to model aggregate-level migration flows? An answer to this question would generate important inputs for both academic and policy-oriented audiences interested in the difficult task of forecasting migration flows. Finally, what are the different times frames in which the processes described in this Chapter take place? Producing fine-grained aggregate-level data on migratory flows would be a necessary step in this regard. The migration stock database recently produced by the UN, based on 5-year intervals between 2000 and 2015, is very promising in this regard. A detailed explanation of the timing (e.g. long term vs. short term) of the processes described in this Chapter can be helpful to star answering questions about causality in the context of international migration flows.

# CONCLUSIONS

This dissertation is devoted to the study of network dynamics that are the direct or indirect result of behaviors observed at the limen of prominent symbolic boundaries. In Chapter 1, I analyze the diffusion of innovations in artificial societies with tunable levels of (cultural) segregation. In Chapter 2, I focus on the diffusion of a health-related innovation using empirical data from an American high school. In Chapter 3, I study the local network configuration of migratory chains; which, in turn, (re)produce the highly stratified system of migration flows in place in the Americas. Throughout the dissertation, I consistently use systems science methods like agent-based models, Stochastic Actor-oriented Models (SAOMs) and Temporal Exponential Random Graph Models (TERGMs).

One of the key arguments in this dissertation has to do with the idea of cultural brokerage. When social actors, either individual or collective, span cultural holes, that means that they are making segregated networks more compact by means of bridging previously disconnected social actors and the cultural worlds to which they belong. A key point in this dissertation is that cultural brokers often are at an advantageous position from a structural point of view (e.g. by means of influencing diffusion dynamics), but could also be at a disadvantage from a social (e.g. psychological, cultural) perspective. Indeed, being in-between, rather than simply *in*, can bring pain, alienation, and distress. That is a major paradox: on the one hand, cultural brokers, and their cross-cultural ties and "translation" abilities, are much needed to make (culturally) segregated networks more compact. On the other hand, when these brokers do traverse cultural boundaries, especially bright symbolic boundaries, they put themselves at great risk.

In fact, Chapter 1 and 2 document the importance of cultural brokers to the widespread diffusion of innovations. At the same time, in those two Chapters I also document how an array of scattered and heterogeneous literatures on adolescent socialization, families, race & ethnicity, migration, and friendship formation systematically point to the burdens of cultural brokerage and liminality more generally.

It is imperative that future work carefully addresses the above mentioned paradox. In particular, a systematic understanding of the determinants of cultural brokerage, and the burdens it carries, will be critical to nurture and encourage the bridging of cultural holes in culturally (e.g. racially) segregated societies. Only after understanding the causes and consequences of cultural brokerage on the lives of cultural brokers themselves will we be able to fully support the bridging of cultural holes. In this dissertation I aimed to put computational social science and systems science methods in conversation with these interesting questions.

Chapter 3 is in line with that very same approach. International migrants' movements throughout the Americas were at the center of the analysis conducted in that last Chapter. In particular, using network-analytic techniques, I studied how aggregate-level data on migration dynamics are useful to describe the system of international migration flows in the Americas during the second half of the 20$^{th}$ century. Results show how triads are key to understand the temporal (re)production of migratory chains that traverse the three different strata that characterize this system.

In that context, it is critical not to lose sight of one key fact: international migrants are vectors of cultural brokerage who typically are, at the same time, at a great disadvantage precisely because of their (cultural) liminality. That is, international migrants embody very

well the paradox behind cultural brokerage mentioned in the paragraphs above. In this regard, I truly believe that the literatures and theories on the causes and consequences of migration reviewed and tested in Chapter 3 are a great starting point to understand the causes and consequences of cultural brokerage more broadly. In that sense, I also believe that my attempt to fully incorporate migration literatures and findings in the critical theory of liminality put forward in Chapters 1 and 2 is a first try at achieving a theoretical synthesis of liminality as a key mechanism for the bridging of cultural holes.

# TABLES

# Table 1.1 Segregation along the Primary Boundary: Modularity

**CONSOLIDATION (C)**

| | | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **H** | 0 | -0.055 | -0.080 | -0.120 | -0.163 | -0.212 | -0.256 | -0.300 | -0.349 | -0.396 | -0.449 | -0.500 |
| **O** | 0.1 | -0.042 | -0.063 | -0.097 | -0.134 | -0.169 | -0.207 | -0.243 | -0.276 | -0.319 | -0.358 | -0.400 |
| **M** | 0.2 | -0.032 | -0.048 | -0.073 | -0.101 | -0.127 | -0.154 | -0.183 | -0.208 | -0.236 | -0.27 | -0.302 |
| **O** | 0.3 | -0.026 | -0.032 | -0.05 | -0.065 | -0.084 | -0.102 | -0.123 | -0.138 | -0.16 | -0.183 | -0.202 |
| **P** | 0.4 | -0.013 | -0.018 | -0.025 | -0.034 | -0.045 | -0.052 | -0.064 | -0.067 | -0.076 | -0.093 | -0.100 |
| **H** | 0.5 | 0.001 | -0.002 | -0.003 | -0.002 | 0.002 | -0.005 | -0.001 | -0.001 | -0.003 | 0.002 | -0.003 |
| **I** | 0.6 | 0.010 | 0.014 | 0.022 | 0.032 | 0.045 | 0.050 | 0.060 | 0.073 | 0.079 | 0.090 | 0.099 |
| **L** | 0.7 | 0.019 | 0.033 | 0.042 | 0.062 | 0.083 | 0.104 | 0.120 | 0.136 | 0.157 | 0.176 | 0.200 |
| **Y** | 0.8 | 0.026 | 0.046 | 0.069 | 0.094 | 0.126 | 0.151 | 0.180 | 0.207 | 0.238 | 0.266 | 0.296 |
| | 0.9 | 0.039 | 0.058 | 0.092 | 0.131 | 0.162 | 0.200 | 0.241 | 0.276 | 0.315 | 0.356 | 0.398 |
| **(H)** | 1 | 0.050 | 0.076 | 0.120 | 0.162 | 0.208 | 0.255 | 0.300 | 0.346 | 0.398 | 0.447 | 0.499 |

Secondary free parameters: $Z = 5$, $N = 300$; $B = 9$; $G = 2$. Cell values averaged over 100 independent realizations.

**Table 1.2 Segregation along the Primary Boundary: Ln(Gross Segregation Index)**

**CONSOLIDATION (C)**

|   |   | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|---|
| **H** | 0 | -0.219 | -0.320 | -0.489 | -0.678 | -0.915 | -1.142 | -1.401 | -1.752 | -2.190 | -2.982 | ∞ |
| **O** | 0.1 | -0.164 | -0.251 | -0.392 | -0.551 | -0.710 | -0.890 | -1.071 | -1.258 | -1.529 | -1.825 | -2.223 |
| **M** | 0.2 | -0.122 | -0.187 | -0.290 | -0.408 | -0.519 | -0.640 | -0.772 | -0.892 | -1.034 | -1.219 | -1.415 |
| **O** | 0.3 | -0.097 | -0.121 | -0.194 | -0.257 | -0.337 | -0.415 | -0.503 | -0.571 | -0.668 | -0.772 | -0.865 |
| **P** | 0.4 | -0.045 | -0.067 | -0.096 | -0.132 | -0.174 | -0.203 | -0.256 | -0.268 | -0.304 | -0.377 | -0.404 |
| **H** | 0.5 | 0.012 | 0.001 | -0.004 | 0.002 | 0.015 | -0.011 | 0.004 | 0.003 | -0.006 | 0.017 | -0.003 |
| **I** | 0.6 | 0.048 | 0.065 | 0.099 | 0.141 | 0.192 | 0.212 | 0.255 | 0.308 | 0.332 | 0.380 | 0.417 |
| **L** | 0.7 | 0.084 | 0.141 | 0.181 | 0.261 | 0.348 | 0.439 | 0.509 | 0.575 | 0.669 | 0.756 | 0.870 |
| **Y** | 0.8 | 0.116 | 0.195 | 0.290 | 0.397 | 0.533 | 0.643 | 0.778 | 0.908 | 1.061 | 1.215 | 1.392 |
|   | 0.9 | 0.166 | 0.245 | 0.387 | 0.555 | 0.694 | 0.871 | 1.080 | 1.276 | 1.521 | 1.822 | 2.224 |
| **(H)** | 1 | 0.212 | 0.320 | 0.506 | 0.693 | 0.910 | 1.156 | 1.422 | 1.744 | 2.232 | 2.963 | ∞ |

Secondary free parameters: **Z** = 5, **N** = 300; **B** = 9; **G** = 2. Cell values averaged over 100 independent realizations.

**Table 2.1. SAOM Estimates Reported by Shoham et al. 2012 and Zhang et al. 2015a Testing Friendship Nominations and BMI Coevolution in Jefferson High**

| Friendship Nomination (Network) Function | b | 95% C. I. | |
|---|---|---|---|
| Basic rate parameter network change | 12.87 | | |
| Out-degree (density) | -3.56 | (-3.64 , | -3.48) |
| Reciprocity | 2.26 | (2.13 , | 2.39) |
| Number of transitive triplets | 0.48 | (0.43 , | 0.53) |
| Same sex | 0.18 | (0.10 , | 0.26) |
| Same grade | 0.49 | (0.41 , | 0.57) |
| Similarity on age | 0.91 | (0.62 , | 1.20) |
| Similarity on income | 0.06 | (-0.23 , | 0.35) |
| BMI ego | -0.007 | (-0.017 , | 0.003) |
| BMI alter | 0.014 | (0.003 , | 0.03) |
| Similarity on BMI | 0.54 | (0.014 , | 0.95) |
| **BMI (Behavior) Function** | | | |
| Basic rate parameter behavior change | 4.17 | | |
| BMI linear shape | 0.16 | (0.11 , | 0.22) |
| BMI quadratic shape | 0.015 | (0.004 , | 0.025) |
| BMI average similarity | 14.1 | (7.76 , | 20.44) |

**Table 3.1 Transitive Triadic Closure**

| 021U Triad | Cyclic Triadic Closure | Probabilistic Mechanism Underlying Cyclicality | Statistic |
|---|---|---|---|
|  |  | Country i tends to send migrants to country k as a function of the existence of triangles of the form [(k→j); (j→i)] | $\sum\limits_{i,j,k} X_{kj}X_{ji}X_{ik},$ |
| ○ Sender (i); ● Any Third Node (j); ◉ Recipient (k) | | | |
| Where $X_{kj}$ = 1 if the ordered pair k→j exits; $X_{jk}$ = 1 if the ordered pair j→i; exists; $X_{ik}$ = 1 if the ordered pair i→k exists | | | |

**Table 3.2 Cyclic Triadic Closure**

| 021U Triad | Cyclic Triadic Closure | Probabilistic Mechanism Underlying Cyclicality | Statistic |
|---|---|---|---|
|  |  | Country i tends to send migrants to country k as a function of the existence of triangles of the form [(k→j); (j→i)] | $\sum_{i,j,k} x_{kj} x_{ji} x_{ik},$ |
| ○ Sender (i);  ● Any Third Node (j); ◉ Recipient (k) Where $X_{kj} = 1$ if the ordered pair k→j exits; $X_{jk} = 1$ if the ordered pair j→i; exists; $X_{ik} = 1$ if the ordered pair i→k exists | | | |

**Table 3.3 Network Descriptive Statistics, Migration Flows in the Americas 1960 – 2000**

| | 1960s | 1970s | 1980s | 1990s |
|---|---|---|---|---|
| **Density** | 0.449 | 0.443 | 0.446 | 0.458 |
| **Centralization** | 0.313 | 0.319 | 0.316 | 0.303 |
| **Mean in-degree (sd)** | 13.91 (8.76) | 13.72 (9.23) | 13.81 (9.16) | 14.19 (7.97) |
| **Number of nodes** | 32 | 32 | 32 | 32 |
| **Number of ties** | 445 | 439 | 442 | 454 |
| **Isolates** | 0 | 0 | 0 | 0 |
| | | | | |
| **Dyad Census** | | | | |
|   **Number of Mutual Dyads** | 122 | 126 | 118 | 133 |
|   **Number of Asymmetric Dyads** | 201 | 187 | 206 | 188 |
|   **Number of Null Dyads** | 173 | 183 | 172 | 175 |
| | | | | |
| | | | | |
| **Observed Network** | | | | |
|   **Number of Transitive Triangles** | 295 | 236 | 345 | 261 |
|   **Number of 021U Triads** | 464 | 520 | 486 | 376 |
|   **Number of Cyclic Triangles** | 21 | 8 | 7 | 15 |
|   **Number of 021C Triads** | 285 | 187 | 242 | 244 |
| | | | | |
| **Simulated Networks*** | | | | |
|   **Mean Number of Transitive Triang.** | 239.15 | 205.99 | 253.81 | 204.58 |
|   **(sd)** | (43.67) | (36.98) | (42.28) | (37.00) |
|   **Mean Number of 021U Triads** | 209.14 | 198.21 | 217.33 | 189.86 |
|   **(sd)** | (23.25) | (22.47) | (24.18) | (21.54) |
|   **Mean Number of Cyclic Triangles** | 79.57 | 67.77 | 84.46 | 67.58 |
|   **(sd)** | (15.51) | (13.78) | (15.97) | (14.17) |
|   **Mean Number of 021C Triads** | 415.14 | 398.72 | 434.34 | 378.18 |
|   **(sd)** | (42.16) | (42.17) | (40.42) | (39.81) |

*Based on 500 dyad census-conditioned random graphs

**Table 3.4 Upper Strata Nodes (i.e. US and Canada) and Triangle Counts**

| Cyclic triangles with at least one upper strata node | 60s | 70s | 80s | 90s |
|---|---|---|---|---|
| Count | 0 | 0 | 0 | 0 |
| (% of all observed cyclic triangles) | (0) | (0) | (0) | (0) |
| **Transitive triangles with at least one upper strata node** | | | | |
| Count | 82 | 56 | 80 | 79 |
| (% of all observed transitive triangles) | (28) | (24) | (23) | (30) |

**Table 3.5 TERGM to Investigate International Migration Flows in the Americas, 1960-2000**

| | Estimates | | Lower Bound CI | Upper Bound CI |
|---|---|---|---|---|
| **Intercept/edges** | 2.583 | ** | 2.456 | 3.232 |
| **Endogenous dependencies** | | | | |
| **Transitive triangles** | 0.140 | ** | 0.093 | 0.192 |
| **Cyclic triangles** | -0.154 | ** | -0.215 | -0.083 |
| **Endogenous controls** | | | | |
| **Mutuality** | 0.409 | ** | 0.204 | 0.597 |
| **Reciprocation** | 0.245 | | -0.024 | 0.544 |
| **Dyadic stability** | 0.478 | ** | 0.280 | 0.844 |
| **In-degree popularity** | 0.173 | + | 0.057 | 0.283 |
| **Out-degree popularity** | -1.293 | ** | -1.622 | -1.253 |
| **Out-degree absolute diff** | -0.649 | + | -1.409 | -0.106 |
| **Exogenous controls** | | | | |
| **Same region** | 1.193 | ** | 1.033 | 1.275 |
| **Same language** | 0.423 | ** | 0.173 | 0.746 |
| **Income * in-degree** | 0.001 | ** | 0.001 | 0.003 |
| **Income * out-degree** | 0.001 | + | 0.001 | 0.002 |
| **Conflict * in-degree** | -0.002 | | -0.005 | 0.004 |
| **Conflict * out-degree** | 0.002 | | -0.003 | 0.007 |

P-value thresholds (two-sided): $+ < 0.1$, $* < 0.05$, $** < 0.001$

**Table 3.6. TERGMs to Investigate International Migration Flows in the Americas by Thresholding Rule Value, 1960-2000**

| | Estimates | | Lower Bound CI | Upper Bound CI | Thresholding rule |
|---|---|---|---|---|---|
| **Endogenous dependencies** | | | | | |
| | | | | | |
| **Transitive triangles** | 0.222 | ** | 0.153 | 0.316 | Top 10 |
| **Cyclic triangles** | -0.245 | ** | -0.433 | -0.149 | destinations |
| | | | | | |
| **Transitive triangles** | 0.140 | ** | 0.093 | 0.192 | Top 15 |
| **Cyclic triangles** | -0.154 | ** | -0.215 | -0.083 | destinations |
| | | | | | |
| **Transitive triangles** | 0.088 | ** | 0.064 | 0.126 | Top 20 |
| **Cyclic triangles** | -0.107 | ** | -0.140 | -0.073 | destinations |

Note: to see all coefficients see Table 3.5 (top 15), and the Appendix, Tables A.3.7 (top 10 & (top 20).
P-value thresholds (two sided): + < 0.1, * < 0.05, ** < 0.001

**FIGURES**

**Figure 1.1 Intercultural Capacity for Brokerage in a Hypothetical Undirected Network**

**Figure 1.2 Representative Sociograms Based on Relevant Levels of Consolidation (C) and Homophily Bias (H) with G = 2**

| No Segregation: Random Graph<br>C = 0, H = 0.5 | Mid-Level Segregation<br>C = 0.5, H = 1 | Full Segregation<br>C = 1, H = 1 |
|---|---|---|
|  |  |  |
| Ln (GSI)=0.026<br>Modularity = 0.005 | Ln (GSI)=1.124<br>Modularity = 0.250 | Ln (GSI)=infinity<br>Modularity = 0.5 |

Secondary free parameters: **Z** = 5, **N** = 300; **B** = 9.

**Figure 1.3 Representative Sociograms Based on Relevant Levels of Consolidation (C) and Homophily Bias (H) with G = 3 & G = 4**

| No Segregation: Random Graph C = 0, H = 0.33, G = 3 | Mid-Level Segregation C = 0.5, H = 1, G=3 | Full Segregation C = 1, H = 1; G=3 |
|---|---|---|
| Ln (GSI)=0 Modularity = -0.002 | Ln (GSI)=1.577 Modularity = 0.366 | Ln (GSI)=infinite Modularity = 0.666 |
| No Segregation: Random Graph C = 0, H = 0.25,G=4 | Mid-Level Segregation C = 0.5, H = 1, G=4 | Full Segregation C = 1, H = 1; G=4 |
| Ln (GSI)=-0.003 Modularity = -0.003 | Ln (GSI)=1.775 Modularity = 0.400 | Ln (GSI)=infinite Modularity = 0.75 |



Secondary free parameters: **Z** = 5, **N** = 300; **B** = 9.

**Figure 1.4 Overall Adoption. Baseline Model (N=300; Z=5; G=5; B=9; $T_{mean}$=0.5; $T_{sd}$=0.05)**

## H O M O P H I L Y

CONSOLIDATION (vertical axis)

### Random

| CONS \ HOM | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.01 | 0.01 | 0.04 | 0.15 | 0.32 | 0.41 | 0.42 | 0.39 | 0.33 | 0.26 | 0.18 |
| 0.9 | 0 | 0.01 | 0.04 | 0.11 | 0.26 | 0.42 | 0.42 | 0.43 | 0.39 | 0.32 | 0.28 |
| 0.8 | 0 | 0.01 | 0.03 | 0.09 | 0.25 | 0.38 | 0.44 | 0.45 | 0.43 | 0.39 | 0.35 |
| 0.7 | 0.01 | 0.01 | 0.02 | 0.06 | 0.19 | 0.32 | 0.42 | 0.47 | 0.43 | 0.42 | 0.41 |
| 0.6 | 0 | 0.01 | 0.02 | 0.05 | 0.12 | 0.25 | 0.36 | 0.41 | 0.45 | 0.46 | 0.44 |
| 0.5 | 0 | 0.01 | 0.02 | 0.04 | 0.09 | 0.19 | 0.3 | 0.35 | 0.43 | 0.44 | 0.47 |
| 0.4 | 0 | 0.01 | 0.01 | 0.02 | 0.05 | 0.11 | 0.18 | 0.25 | 0.27 | 0.32 | 0.36 |
| 0.3 | 0 | 0 | 0.01 | 0.02 | 0.04 | 0.06 | 0.09 | 0.13 | 0.15 | 0.15 | 0.19 |
| 0.2 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 | 0.06 | 0.05 |
| 0.1 | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 |
| 0 | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 |

### Popularity (i.e. Degree)

| CONS \ HOM | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.01 | 0.03 | 0.09 | 0.26 | 0.5 | 0.62 | 0.62 | 0.6 | 0.46 | 0.34 | 0.16 |
| 0.9 | 0.01 | 0.03 | 0.07 | 0.22 | 0.49 | 0.63 | 0.69 | 0.63 | 0.57 | 0.53 | 0.4 |
| 0.8 | 0.01 | 0.02 | 0.06 | 0.18 | 0.42 | 0.62 | 0.7 | 0.68 | 0.67 | 0.66 | 0.56 |
| 0.7 | 0.01 | 0.02 | 0.06 | 0.14 | 0.3 | 0.52 | 0.65 | 0.69 | 0.68 | 0.71 | 0.66 |
| 0.6 | 0.01 | 0.02 | 0.04 | 0.11 | 0.25 | 0.46 | 0.63 | 0.68 | 0.73 | 0.74 | 0.69 |
| 0.5 | 0.01 | 0.01 | 0.03 | 0.09 | 0.18 | 0.34 | 0.5 | 0.63 | 0.69 | 0.7 | 0.72 |
| 0.4 | 0.01 | 0.01 | 0.03 | 0.06 | 0.12 | 0.22 | 0.37 | 0.46 | 0.54 | 0.59 | 0.64 |
| 0.3 | 0.01 | 0.01 | 0.02 | 0.04 | 0.08 | 0.14 | 0.19 | 0.26 | 0.32 | 0.34 | 0.39 |
| 0.2 | 0.01 | 0.01 | 0.01 | 0.03 | 0.05 | 0.08 | 0.1 | 0.12 | 0.13 | 0.13 | 0.13 |
| 0.1 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 | 0 |

### Structural Brokerage (i.e. Betweenness)

| CONS \ HOM | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.02 | 0.03 | 0.08 | 0.27 | 0.52 | 0.67 | 0.68 | 0.68 | 0.62 | 0.59 | 0.17 |
| 0.9 | 0.01 | 0.03 | 0.08 | 0.22 | 0.49 | 0.65 | 0.74 | 0.71 | 0.7 | 0.66 | 0.64 |
| 0.8 | 0.01 | 0.02 | 0.06 | 0.16 | 0.41 | 0.63 | 0.69 | 0.71 | 0.72 | 0.68 | 0.7 |
| 0.7 | 0.01 | 0.02 | 0.05 | 0.14 | 0.33 | 0.56 | 0.69 | 0.73 | 0.71 | 0.74 | 0.72 |
| 0.6 | 0.01 | 0.02 | 0.04 | 0.11 | 0.26 | 0.47 | 0.6 | 0.68 | 0.74 | 0.75 | 0.76 |
| 0.5 | 0.01 | 0.01 | 0.03 | 0.08 | 0.19 | 0.35 | 0.51 | 0.63 | 0.69 | 0.71 | 0.75 |
| 0.4 | 0.01 | 0.01 | 0.03 | 0.06 | 0.12 | 0.22 | 0.35 | 0.47 | 0.55 | 0.6 | 0.64 |
| 0.3 | 0.01 | 0.01 | 0.02 | 0.04 | 0.08 | 0.14 | 0.2 | 0.26 | 0.33 | 0.34 | 0.39 |
| 0.2 | 0.01 | 0.01 | 0.01 | 0.03 | 0.05 | 0.07 | 0.1 | 0.12 | 0.13 | 0.13 | 0.15 |
| 0.1 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.05 | 0.05 | 0.04 | 0.03 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0 | 0 |

### Cultural Brokerage

| CONS \ HOM | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.02 | 0.03 | 0.08 | 0.27 | 0.56 | 0.7 | 0.77 | 0.75 | 0.67 | 0.57 | 0.18 |
| 0.9 | 0.01 | 0.02 | 0.07 | 0.22 | 0.52 | 0.69 | 0.75 | 0.76 | 0.76 | 0.73 | 0.66 |
| 0.8 | 0.01 | 0.02 | 0.06 | 0.19 | 0.43 | 0.65 | 0.77 | 0.77 | 0.79 | 0.81 | 0.74 |
| 0.7 | 0.01 | 0.02 | 0.05 | 0.13 | 0.35 | 0.57 | 0.7 | 0.78 | 0.79 | 0.81 | 0.8 |
| 0.6 | 0.01 | 0.02 | 0.04 | 0.11 | 0.23 | 0.49 | 0.64 | 0.75 | 0.77 | 0.81 | 0.8 |
| 0.5 | 0.01 | 0.01 | 0.03 | 0.08 | 0.19 | 0.38 | 0.52 | 0.67 | 0.73 | 0.74 | 0.79 |
| 0.4 | 0.01 | 0.01 | 0.02 | 0.06 | 0.13 | 0.24 | 0.37 | 0.49 | 0.56 | 0.62 | 0.67 |
| 0.3 | 0.01 | 0.01 | 0.02 | 0.05 | 0.08 | 0.14 | 0.22 | 0.27 | 0.32 | 0.38 | 0.41 |
| 0.2 | 0 | 0.01 | 0.01 | 0.03 | 0.05 | 0.07 | 0.1 | 0.12 | 0.14 | 0.13 | 0.13 |
| 0.1 | 0 | 0 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.05 | 0.05 | 0.04 | 0.03 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 | 0 |

**Adoption** (color scale: 0 — 0.5 — 1)

# Figure 1.5 In-Group Adoption. Baseline Model (N=300; Z=5; G=5; B=9; $T_{mean}$=0.5; $T_{sd}$=0.05)



**H O M O P H I L Y**

**C O N S O L I D A T I O N**

### Random

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.02 | 0.09 | 0.27 | 0.56 | 0.81 | 0.9 | 0.95 | 0.98 | 0.99 | 1 | 1 |
| 0.01 | 0.02 | 0.07 | 0.19 | 0.45 | 0.76 | 0.84 | 0.95 | 0.96 | 0.97 | 1 | 0.9 |
| 0 | 0.01 | 0.05 | 0.15 | 0.37 | 0.67 | 0.77 | 0.9 | 0.94 | 0.97 | 0.96 | 0.8 |
| 0.01 | 0.01 | 0.03 | 0.11 | 0.32 | 0.51 | 0.71 | 0.82 | 0.91 | 0.88 | 0.96 | 0.7 |
| 0 | 0.01 | 0.03 | 0.09 | 0.19 | 0.4 | 0.58 | 0.7 | 0.83 | 0.82 | 0.91 | 0.6 |
| 0 | 0.01 | 0.02 | 0.06 | 0.12 | 0.3 | 0.43 | 0.53 | 0.66 | 0.74 | 0.79 | 0.5 |
| 0 | 0.01 | 0.01 | 0.03 | 0.07 | 0.17 | 0.24 | 0.41 | 0.39 | 0.55 | 0.55 | 0.4 |
| 0 | 0.01 | 0.01 | 0.02 | 0.04 | 0.07 | 0.12 | 0.14 | 0.21 | 0.21 | 0.27 | 0.3 |
| 0 | 0 | 0.01 | 0.01 | 0.03 | 0.03 | 0.05 | 0.05 | 0.05 | 0.07 | 0.06 | 0.2 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 | 0.1 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

### Popularity (i.e. Degree)

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.02 | 0.04 | 0.16 | 0.43 | 0.71 | 0.87 | 0.94 | 0.97 | 0.99 | 1 | 1 | 1 |
| 0.02 | 0.04 | 0.13 | 0.36 | 0.66 | 0.81 | 0.9 | 0.96 | 0.97 | 0.99 | 1 | 0.9 |
| 0.02 | 0.03 | 0.09 | 0.29 | 0.58 | 0.79 | 0.88 | 0.94 | 0.96 | 0.98 | 0.99 | 0.8 |
| 0.01 | 0.03 | 0.08 | 0.24 | 0.47 | 0.7 | 0.84 | 0.91 | 0.93 | 0.96 | 0.97 | 0.7 |
| 0.01 | 0.02 | 0.06 | 0.18 | 0.34 | 0.58 | 0.77 | 0.85 | 0.9 | 0.92 | 0.95 | 0.6 |
| 0.01 | 0.02 | 0.04 | 0.1 | 0.26 | 0.47 | 0.64 | 0.75 | 0.83 | 0.86 | 0.89 | 0.5 |
| 0.01 | 0.01 | 0.03 | 0.07 | 0.15 | 0.3 | 0.43 | 0.56 | 0.68 | 0.72 | 0.75 | 0.4 |
| 0.01 | 0.01 | 0.02 | 0.05 | 0.09 | 0.18 | 0.25 | 0.3 | 0.36 | 0.44 | 0.49 | 0.3 |
| 0.01 | 0.01 | 0.01 | 0.03 | 0.05 | 0.06 | 0.11 | 0.11 | 0.12 | 0.12 | 0.11 | 0.2 |
| 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.04 | 0.02 | 0.02 | 0.1 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 | 0 |

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

### Structural Brokerage (i.e. Betweenness)

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.02 | 0.04 | 0.15 | 0.39 | 0.71 | 0.85 | 0.93 | 0.97 | 0.99 | 0.99 | 1 | 1 |
| 0.01 | 0.04 | 0.12 | 0.35 | 0.64 | 0.82 | 0.92 | 0.95 | 0.97 | 0.99 | 0.99 | 0.9 |
| 0.02 | 0.03 | 0.1 | 0.27 | 0.58 | 0.76 | 0.88 | 0.94 | 0.96 | 0.98 | 0.98 | 0.8 |
| 0.01 | 0.02 | 0.08 | 0.21 | 0.43 | 0.71 | 0.84 | 0.91 | 0.92 | 0.95 | 0.98 | 0.7 |
| 0.01 | 0.02 | 0.07 | 0.19 | 0.36 | 0.59 | 0.74 | 0.84 | 0.9 | 0.93 | 0.95 | 0.6 |
| 0.01 | 0.02 | 0.05 | 0.11 | 0.28 | 0.45 | 0.66 | 0.78 | 0.83 | 0.87 | 0.89 | 0.5 |
| 0.01 | 0.01 | 0.03 | 0.06 | 0.16 | 0.28 | 0.45 | 0.55 | 0.65 | 0.76 | 0.77 | 0.4 |
| 0.01 | 0.01 | 0.02 | 0.05 | 0.09 | 0.15 | 0.26 | 0.32 | 0.37 | 0.46 | 0.45 | 0.3 |
| 0 | 0.01 | 0.01 | 0.03 | 0.06 | 0.08 | 0.09 | 0.12 | 0.11 | 0.13 | 0.16 | 0.2 |
| 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.04 | 0.04 | 0.04 | 0.02 | 0.02 | 0.1 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0 | 0.01 | 0 | 0 | 0 | 0 |

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

### Cultural Brokerage

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.02 | 0.05 | 0.14 | 0.42 | 0.7 | 0.86 | 0.94 | 0.97 | 0.99 | 0.99 | 1 | 1 |
| 0.02 | 0.03 | 0.12 | 0.31 | 0.66 | 0.81 | 0.9 | 0.95 | 0.98 | 0.99 | 1 | 0.9 |
| 0.01 | 0.02 | 0.09 | 0.27 | 0.58 | 0.79 | 0.89 | 0.93 | 0.96 | 0.98 | 0.99 | 0.8 |
| 0.01 | 0.02 | 0.08 | 0.21 | 0.46 | 0.72 | 0.83 | 0.91 | 0.94 | 0.95 | 0.97 | 0.7 |
| 0.01 | 0.02 | 0.05 | 0.16 | 0.31 | 0.61 | 0.75 | 0.83 | 0.9 | 0.92 | 0.95 | 0.6 |
| 0.01 | 0.02 | 0.04 | 0.09 | 0.23 | 0.43 | 0.63 | 0.78 | 0.8 | 0.86 | 0.9 | 0.5 |
| 0.01 | 0.01 | 0.03 | 0.06 | 0.17 | 0.28 | 0.41 | 0.59 | 0.65 | 0.71 | 0.77 | 0.4 |
| 0.01 | 0.01 | 0.02 | 0.05 | 0.08 | 0.16 | 0.23 | 0.31 | 0.38 | 0.46 | 0.44 | 0.3 |
| 0 | 0.01 | 0.02 | 0.02 | 0.05 | 0.07 | 0.08 | 0.12 | 0.13 | 0.13 | 0.12 | 0.2 |
| 0.01 | 0 | 0.01 | 0.02 | 0.02 | 0.03 | 0.04 | 0.04 | 0.03 | 0.03 | 0.02 | 0.1 |
| 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 | 0 |

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

**Adoption**

0 0.5 1

**Figure 1.6 Out-Group Adoption. Baseline Model (N=300; Z=5; G=5; B=9; $T_{mean}=0.5$; $T_{sd}=0.05$)**

H O M O P H I L Y

CONSOLIDATION

**Random**

| 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.01 | 0.03 | 0.12 | 0.27 | 0.32 | 0.31 | 0.27 | 0.18 | 0.1 | 0 | 1 |
| 0 | 0.01 | 0.03 | 0.09 | 0.21 | 0.34 | 0.32 | 0.31 | 0.26 | 0.18 | 0.12 | 0.9 |
| 0 | 0.01 | 0.03 | 0.07 | 0.22 | 0.31 | 0.36 | 0.35 | 0.31 | 0.26 | 0.21 | 0.8 |
| 0 | 0.01 | 0.02 | 0.04 | 0.16 | 0.28 | 0.35 | 0.39 | 0.32 | 0.32 | 0.28 | 0.7 |
| 0 | 0.01 | 0.01 | 0.04 | 0.1 | 0.21 | 0.31 | 0.34 | 0.36 | 0.38 | 0.33 | 0.6 |
| 0 | 0 | 0.02 | 0.03 | 0.08 | 0.16 | 0.27 | 0.31 | 0.38 | 0.37 | 0.39 | 0.5 |
| 0 | 0 | 0.01 | 0.02 | 0.05 | 0.1 | 0.16 | 0.22 | 0.24 | 0.26 | 0.32 | 0.4 |
| 0 | 0 | 0.01 | 0.02 | 0.04 | 0.05 | 0.09 | 0.13 | 0.13 | 0.14 | 0.18 | 0.3 |
| 0 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 | 0.06 | 0.05 | 0.2 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.1 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 | 0 |

**Popularity (i.e. Degree)**

| 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.02 | 0.07 | 0.22 | 0.45 | 0.57 | 0.55 | 0.52 | 0.35 | 0.2 | 0 | 1 |
| 0.01 | 0.03 | 0.06 | 0.18 | 0.45 | 0.6 | 0.65 | 0.57 | 0.49 | 0.44 | 0.28 | 0.9 |
| 0.01 | 0.02 | 0.05 | 0.15 | 0.38 | 0.58 | 0.66 | 0.62 | 0.61 | 0.59 | 0.48 | 0.8 |
| 0.01 | 0.02 | 0.05 | 0.12 | 0.26 | 0.48 | 0.61 | 0.64 | 0.62 | 0.66 | 0.6 | 0.7 |
| 0.01 | 0.02 | 0.03 | 0.1 | 0.22 | 0.43 | 0.6 | 0.64 | 0.69 | 0.69 | 0.64 | 0.6 |
| 0.01 | 0.01 | 0.03 | 0.08 | 0.16 | 0.32 | 0.47 | 0.6 | 0.66 | 0.66 | 0.69 | 0.5 |
| 0.01 | 0.01 | 0.03 | 0.05 | 0.12 | 0.2 | 0.36 | 0.44 | 0.51 | 0.56 | 0.61 | 0.4 |
| 0.01 | 0.01 | 0.02 | 0.04 | 0.08 | 0.13 | 0.17 | 0.25 | 0.31 | 0.32 | 0.37 | 0.3 |
| 0.01 | 0.01 | 0.01 | 0.03 | 0.05 | 0.08 | 0.1 | 0.12 | 0.13 | 0.13 | 0.14 | 0.2 |
| 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.1 |
| 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0 | 0 |

**Structural Brokerage (i.e. Betweenness)**

| 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.02 | 0.03 | 0.07 | 0.25 | 0.48 | 0.63 | 0.62 | 0.61 | 0.54 | 0.5 | 0 | 1 |
| 0.01 | 0.02 | 0.07 | 0.19 | 0.46 | 0.62 | 0.7 | 0.66 | 0.64 | 0.59 | 0.56 | 0.9 |
| 0.01 | 0.02 | 0.05 | 0.13 | 0.37 | 0.59 | 0.65 | 0.66 | 0.66 | 0.61 | 0.64 | 0.8 |
| 0.01 | 0.02 | 0.05 | 0.12 | 0.31 | 0.53 | 0.65 | 0.69 | 0.66 | 0.7 | 0.67 | 0.7 |
| 0.01 | 0.02 | 0.04 | 0.09 | 0.24 | 0.45 | 0.57 | 0.64 | 0.71 | 0.71 | 0.72 | 0.6 |
| 0.01 | 0.01 | 0.03 | 0.07 | 0.17 | 0.33 | 0.47 | 0.6 | 0.65 | 0.67 | 0.72 | 0.5 |
| 0.01 | 0.01 | 0.03 | 0.06 | 0.12 | 0.2 | 0.33 | 0.45 | 0.53 | 0.56 | 0.61 | 0.4 |
| 0.01 | 0.01 | 0.02 | 0.04 | 0.08 | 0.13 | 0.19 | 0.24 | 0.32 | 0.31 | 0.37 | 0.3 |
| 0.01 | 0.01 | 0.01 | 0.03 | 0.05 | 0.07 | 0.11 | 0.13 | 0.14 | 0.13 | 0.14 | 0.2 |
| 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.1 |
| 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0 | 0 |

**Cultural Brokerage**

| 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.02 | 0.07 | 0.24 | 0.53 | 0.66 | 0.73 | 0.7 | 0.6 | 0.48 | 0 | 1 |
| 0.01 | 0.02 | 0.06 | 0.2 | 0.48 | 0.66 | 0.72 | 0.72 | 0.71 | 0.68 | 0.58 | 0.9 |
| 0.01 | 0.02 | 0.05 | 0.17 | 0.39 | 0.62 | 0.74 | 0.73 | 0.75 | 0.77 | 0.68 | 0.8 |
| 0.01 | 0.02 | 0.04 | 0.11 | 0.33 | 0.53 | 0.67 | 0.75 | 0.76 | 0.78 | 0.77 | 0.7 |
| 0.01 | 0.02 | 0.04 | 0.1 | 0.22 | 0.47 | 0.61 | 0.73 | 0.74 | 0.78 | 0.76 | 0.6 |
| 0.01 | 0.01 | 0.03 | 0.08 | 0.18 | 0.36 | 0.49 | 0.65 | 0.71 | 0.72 | 0.76 | 0.5 |
| 0.01 | 0.01 | 0.02 | 0.05 | 0.12 | 0.24 | 0.36 | 0.47 | 0.53 | 0.6 | 0.65 | 0.4 |
| 0.01 | 0.01 | 0.02 | 0.05 | 0.08 | 0.13 | 0.22 | 0.26 | 0.31 | 0.36 | 0.4 | 0.3 |
| 0 | 0.01 | 0.01 | 0.03 | 0.05 | 0.07 | 0.1 | 0.12 | 0.14 | 0.13 | 0.13 | 0.2 |
| 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 | 0.1 |
| 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0 | 0 |

**Adoption**

0  0.5  1

123

**Figure 1.7 Effectiveness of Cultural Brokerage vs. Other Strategies (Random, Popularity, Structural Brokerage – i.e. Betweenness –)**

## H O M O P H I L Y

### (Cultural Brokerage) – (Random)

CONSOLIDATION (rows) × HOMOPHILY (columns)

| Consolidation | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.01 | 0.01 | 0.04 | 0.12 | 0.26 | 0.35 | 0.42 | 0.43 | 0.42 | 0.38 | 0 |
| 0.9 | 0.01 | 0.01 | 0.04 | 0.12 | 0.27 | 0.32 | 0.4 | 0.41 | 0.45 | 0.5 | 0.46 |
| 0.8 | 0.01 | 0.01 | 0.02 | 0.1 | 0.18 | 0.3 | 0.38 | 0.38 | 0.44 | 0.51 | 0.48 |
| 0.7 | 0 | 0.01 | 0.03 | 0.07 | 0.17 | 0.26 | 0.32 | 0.36 | 0.44 | 0.46 | 0.49 |
| 0.6 | 0.01 | 0.01 | 0.03 | 0.06 | 0.11 | 0.26 | 0.31 | 0.38 | 0.38 | 0.4 | 0.43 |
| 0.5 | 0.01 | 0.01 | 0.01 | 0.04 | 0.1 | 0.2 | 0.22 | 0.33 | 0.33 | 0.34 | 0.37 |
| 0.4 | 0 | 0.01 | 0.02 | 0.03 | 0.07 | 0.14 | 0.19 | 0.25 | 0.29 | 0.33 | 0.33 |
| 0.3 | 0 | 0.01 | 0.01 | 0.02 | 0.04 | 0.08 | 0.13 | 0.13 | 0.18 | 0.22 | 0.22 |
| 0.2 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.06 | 0.07 | 0.08 | 0.07 | 0.07 |
| 0.1 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 |
| 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0 |

### (Cultural Brokerage) – (Popularity)

| Consolidation | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.02 | 0.08 | 0.1 | 0.18 | 0.18 | 0.25 | 0.27 | 0 |
| 0.9 | 0 | 0 | 0 | 0.02 | 0.04 | 0.06 | 0.07 | 0.15 | 0.22 | 0.23 | 0.3 |
| 0.8 | 0 | 0 | 0 | 0.02 | 0.01 | 0.03 | 0.08 | 0.11 | 0.14 | 0.18 | 0.21 |
| 0.7 | 0 | 0 | -0.01 | -0.01 | 0.06 | 0.05 | 0.07 | 0.11 | 0.14 | 0.12 | 0.17 |
| 0.6 | 0 | 0 | 0.01 | 0 | -0.01 | 0.04 | 0.01 | 0.08 | 0.04 | 0.09 | 0.12 |
| 0.5 | 0 | 0 | 0 | 0 | 0.01 | 0.05 | 0.02 | 0.04 | 0.05 | 0.05 | 0.08 |
| 0.4 | 0 | 0 | 0 | 0 | 0 | 0.04 | 0 | 0.03 | 0.02 | 0.04 | 0.04 |
| 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0.05 | 0.01 | 0 | 0.04 | 0.03 |
| 0.2 | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0 | 0 | 0 | 0 | -0.01 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Cultural Brokerage) – (Structural Brokerage)

| Consolidation | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | -0.01 | 0.05 | 0.04 | 0.11 | 0.08 | 0.06 | -0.02 | 0 |
| 0.9 | 0 | 0 | 0 | 0.02 | 0.03 | 0.04 | 0.02 | 0.06 | 0.07 | 0.08 | 0.02 |
| 0.8 | 0 | 0 | 0 | 0.04 | 0.02 | 0.02 | 0.09 | 0.07 | 0.09 | 0.16 | 0.04 |
| 0.7 | 0 | 0 | 0 | -0.01 | 0.01 | 0.01 | 0.02 | 0.06 | 0.1 | 0.08 | 0.1 |
| 0.6 | 0 | 0 | 0.01 | 0.01 | -0.02 | 0.02 | 0.04 | 0.09 | 0.03 | 0.07 | 0.04 |
| 0.5 | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.02 | 0.04 | 0.05 | 0.05 | 0.05 |
| 0.4 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.03 | 0.02 | 0.01 | 0.04 | 0.04 |
| 0.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.02 | 0 | 0.04 | 0.03 |
| 0.2 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0 | 0.01 | -0.02 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Baseline Model**
(N=300; Z=5; G=5; B=9; $T_{mean}=0.5$; $T_{sd}=0.05$)

**Adoption**

0    0.5    1

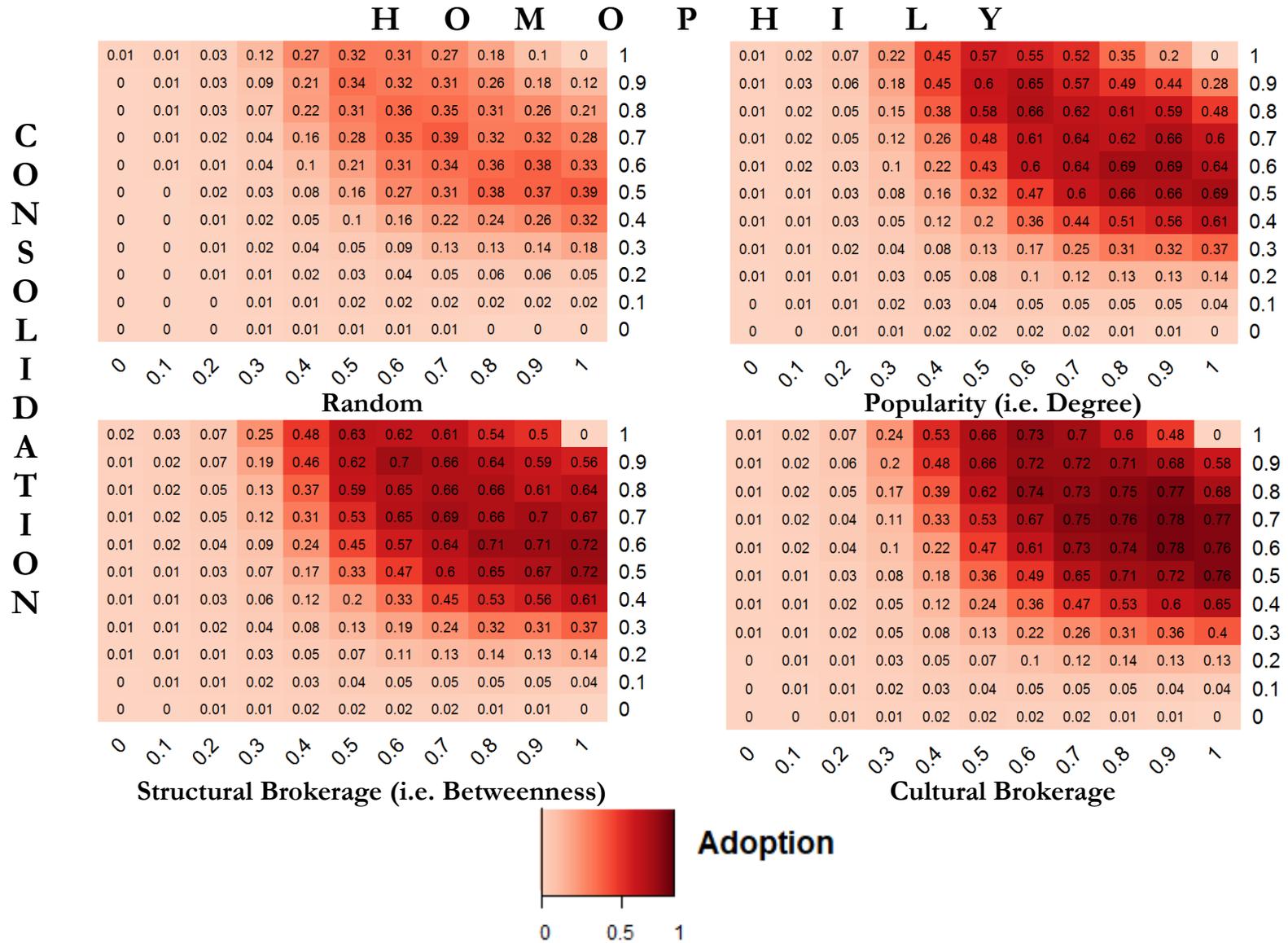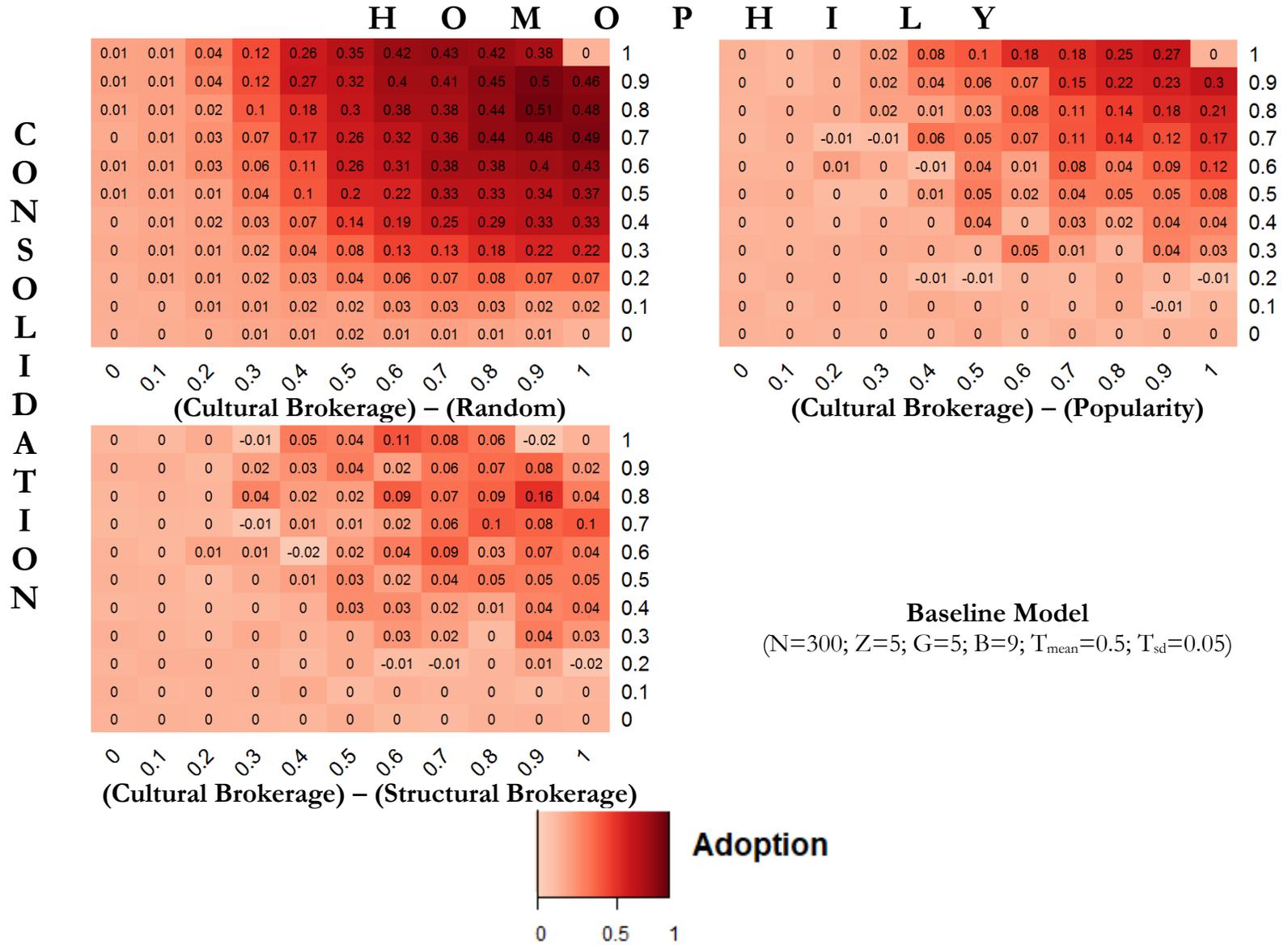# Figure 1.8 Effectiveness of Null Brokerage vs. Other Strategies (Random, Popularity, Structural Brokerage – i.e. Betweenness –)

## H O M O P H I L Y
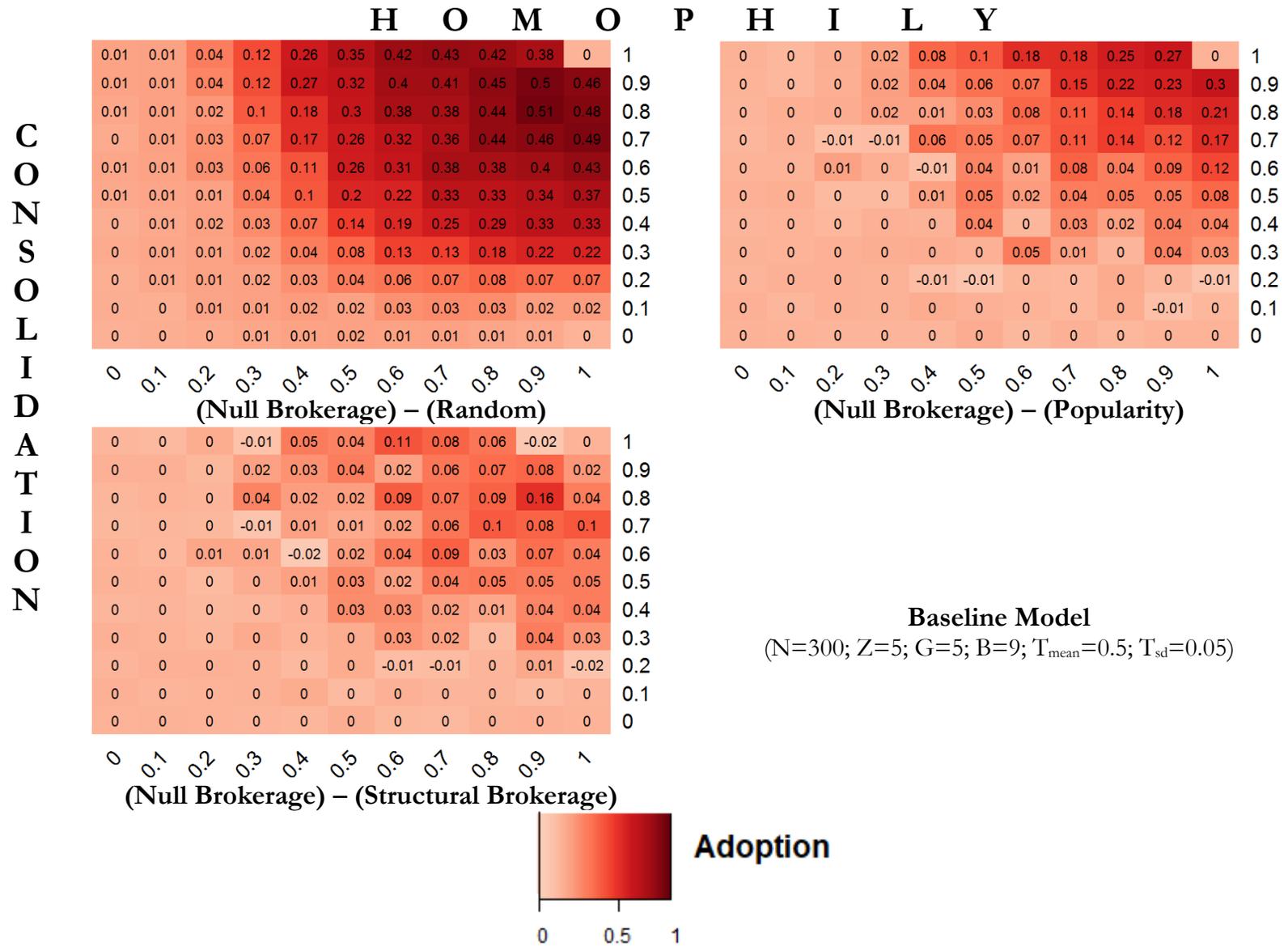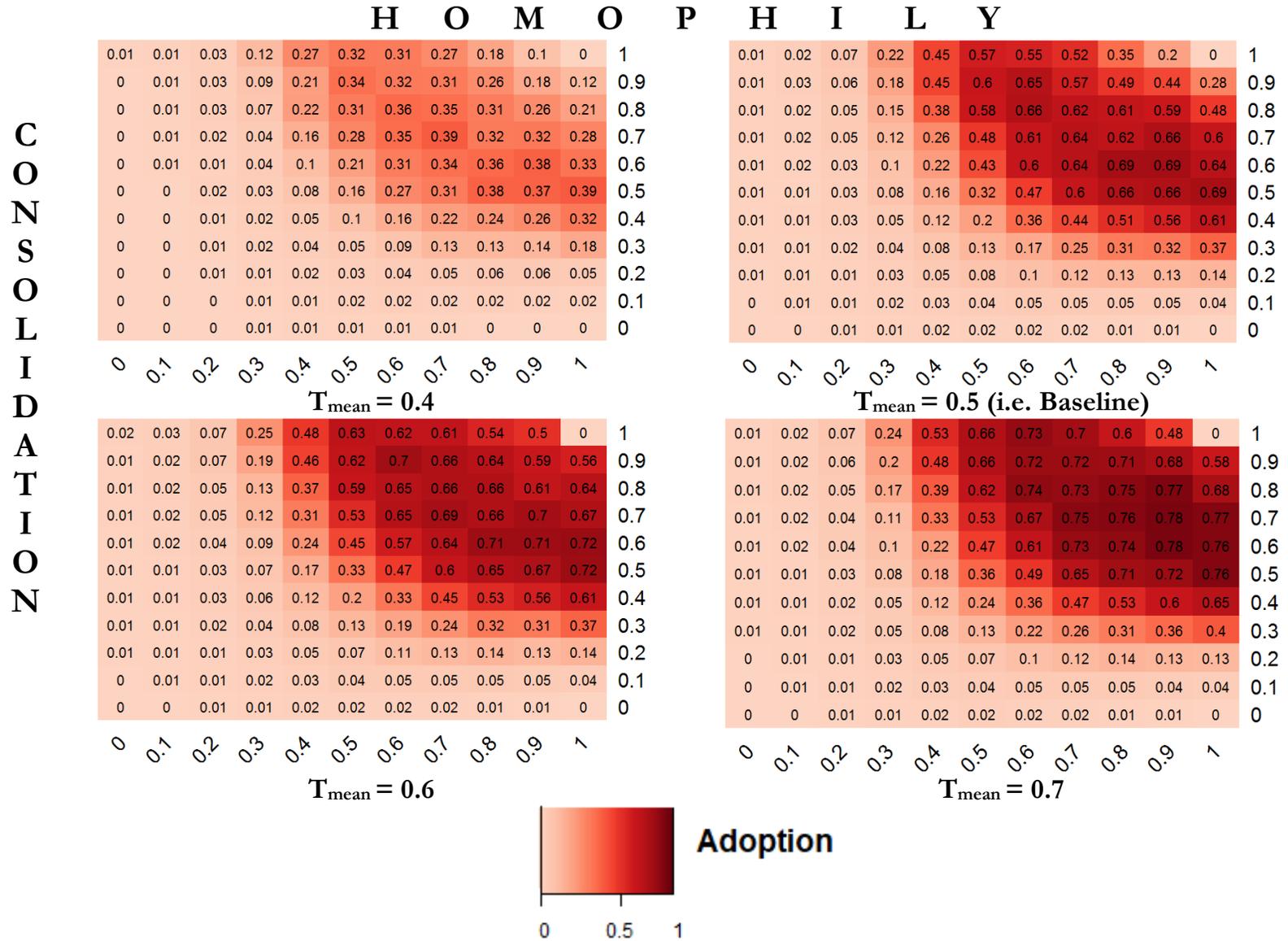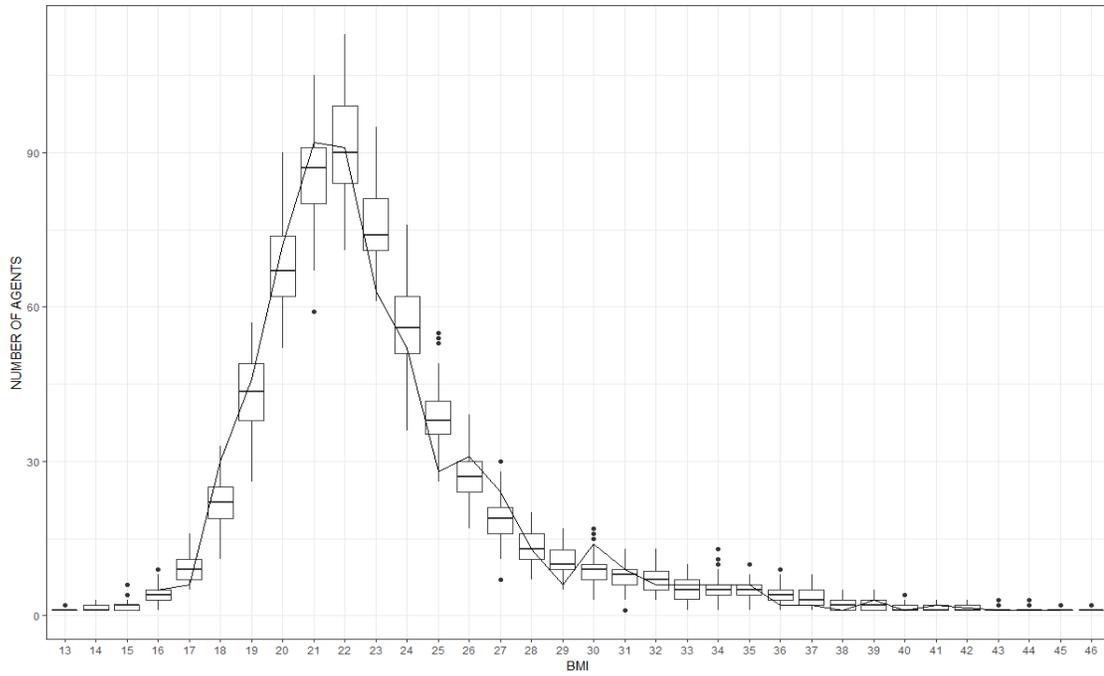
**CONSOLIDATION**

### (Null Brokerage) – (Random)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 0.01 | 0.04 | 0.12 | 0.26 | 0.35 | 0.42 | 0.43 | 0.42 | 0.38 | 0 | 1 |
| | 0.01 | 0.01 | 0.04 | 0.12 | 0.27 | 0.32 | 0.4 | 0.41 | 0.45 | 0.5 | 0.46 | 0.9 |
| | 0.01 | 0.01 | 0.02 | 0.1 | 0.18 | 0.3 | 0.38 | 0.38 | 0.44 | 0.51 | 0.48 | 0.8 |
| | 0 | 0.01 | 0.03 | 0.07 | 0.17 | 0.26 | 0.32 | 0.36 | 0.44 | 0.46 | 0.49 | 0.7 |
| | 0.01 | 0.01 | 0.03 | 0.06 | 0.11 | 0.26 | 0.31 | 0.38 | 0.38 | 0.4 | 0.43 | 0.6 |
| | 0.01 | 0.01 | 0.01 | 0.04 | 0.1 | 0.2 | 0.22 | 0.33 | 0.33 | 0.34 | 0.37 | 0.5 |
| | 0 | 0.01 | 0.02 | 0.03 | 0.07 | 0.14 | 0.19 | 0.25 | 0.29 | 0.33 | 0.33 | 0.4 |
| | 0 | 0.01 | 0.01 | 0.02 | 0.04 | 0.08 | 0.13 | 0.13 | 0.18 | 0.22 | 0.22 | 0.3 |
| | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.06 | 0.07 | 0.08 | 0.07 | 0.07 | 0.2 |
| | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.1 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 |

### (Null Brokerage) – (Popularity)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | 0.02 | 0.08 | 0.1 | 0.18 | 0.18 | 0.25 | 0.27 | 0 | 1 |
| | 0 | 0 | 0 | 0.02 | 0.04 | 0.06 | 0.07 | 0.15 | 0.22 | 0.23 | 0.3 | 0.9 |
| | 0 | 0 | 0 | 0.02 | 0.01 | 0.03 | 0.08 | 0.11 | 0.14 | 0.18 | 0.21 | 0.8 |
| | 0 | 0 | -0.01 | -0.01 | 0.06 | 0.05 | 0.07 | 0.11 | 0.14 | 0.12 | 0.17 | 0.7 |
| | 0 | 0 | 0.01 | 0 | -0.01 | 0.04 | 0.01 | 0.08 | 0.04 | 0.09 | 0.12 | 0.6 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.05 | 0.02 | 0.04 | 0.05 | 0.05 | 0.08 | 0.5 |
| | 0 | 0 | 0 | 0 | 0 | 0.04 | 0 | 0.03 | 0.02 | 0.04 | 0.04 | 0.4 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0.05 | 0.01 | 0 | 0.04 | 0.03 | 0.3 |
| | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0 | 0 | 0 | 0 | -0.01 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Null Brokerage) – (Structural Brokerage)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | -0.01 | 0.05 | 0.04 | 0.11 | 0.08 | 0.06 | -0.02 | 0 | 1 |
| | 0 | 0 | 0 | 0.02 | 0.03 | 0.04 | 0.02 | 0.06 | 0.07 | 0.08 | 0.02 | 0.9 |
| | 0 | 0 | 0 | 0.04 | 0.02 | 0.02 | 0.09 | 0.07 | 0.09 | 0.16 | 0.04 | 0.8 |
| | 0 | 0 | 0 | -0.01 | 0.01 | 0.01 | 0.02 | 0.06 | 0.1 | 0.08 | 0.1 | 0.7 |
| | 0 | 0 | 0.01 | 0.01 | -0.02 | 0.02 | 0.04 | 0.09 | 0.03 | 0.07 | 0.04 | 0.6 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.02 | 0.04 | 0.05 | 0.05 | 0.05 | 0.5 |
| | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.03 | 0.02 | 0.01 | 0.04 | 0.04 | 0.4 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.02 | 0 | 0.04 | 0.03 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0 | 0.01 | -0.02 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Baseline Model**
(N=300; Z=5; G=5; B=9; $T_{mean}$=0.5; $T_{sd}$=0.05)

**Adoption**

0    0.5    1

**Figure 1.9 Robustness Check for $T_{mean}$: Cultural vs. Structural Brokerage (N=300; Z=5; G=5; B=9; $T_{sd}$=0.05)**



H  O  M  O  P  H  I  L  Y

CONSOLIDATION

$T_{mean} = 0.4$

$T_{mean} = 0.5$ (i.e. Baseline)

$T_{mean} = 0.6$

$T_{mean} = 0.7$
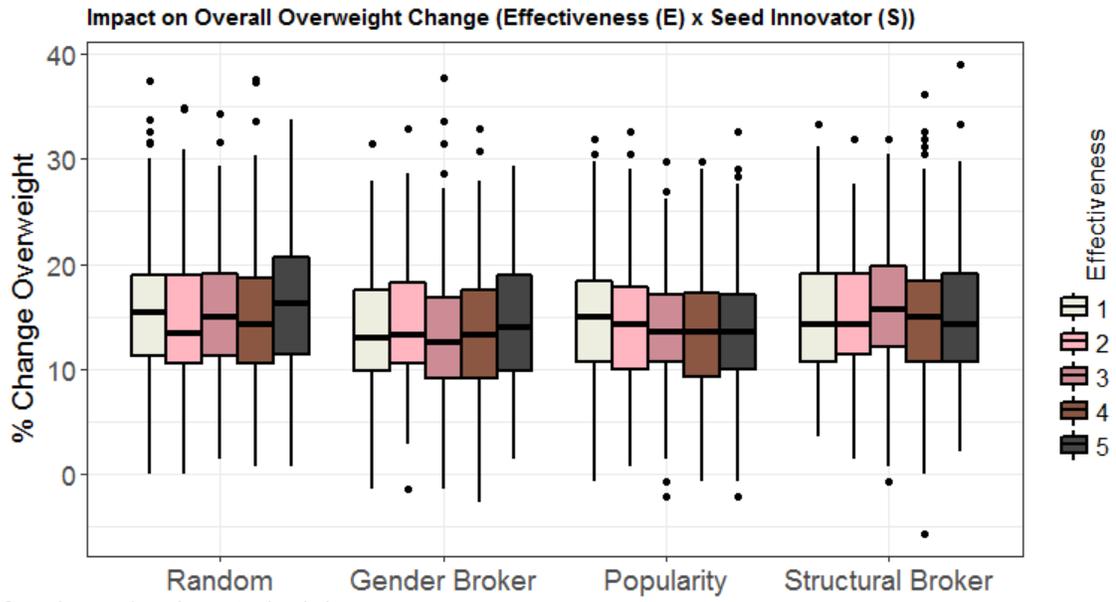
Adoption

0    0.5    1

126

**Figure 2.1 BMI in the Observed (Solid Line) and Simulated (Box Plots) Jefferson High in Wave 2**



Box plots are based on 100 simulations.

**Figure 2.2 Overall Overweight Change (OW<sub>overall</sub>) in Jefferson High by Effectiveness and Seed Innovator Type**



Box plots are based on 250 simulations

**Figure 2.3 Out-group Overweight Change (OW$_{out}$) Across the Gender Boundary in Jefferson High by Effectiveness (E) and Seed Innovator Type (S)**



Box plots are based on 250 simulations

**Figure 2.4. Out-group Overweight Change (OW$_{out}$) Across Several Boundaries in Jefferson High by Effectiveness (E) and Seed Innovator Type (S)**



Impact on Outgroup Overweight Change (Effectiveness (E) x Seed Innovator (S))

Box plots are based on 250 simulations

**Figure 2.5. In-group Overweight Change (OW$_{in}$) Across Several Boundaries in Jefferson High by Effectiveness (E) and Seed Innovator Type (S)**



Box plots are based on 250 simulations

**Figure 3.1 Migration Flows in Central America and the Caribbean by Decade, 1960-2000**



**Note.** Countries can be identified as follows: Belize (BZ); Costa Rica (CR); El Salvador (SV); Guatemala (GT); Honduras (HN); Nicaragua (NI); Panama (PA); Antigua and Barbuda (AG); Aruba (AW); the Bahamas (BS); Barbados (BB); Cuba (CU); Dominican Republic (DO); French Guiana (GF); Grenada (WG); Guadalupe (GP); Guyana (GY); Haiti (HT); Jamaica (JA); Martinique (MQ); Puerto Rico (PR); St. Lucia (WL); St. Vincent and the Grenadines (WV); Suriname (SR); Trinidad and Tobago (TT).

**Figure 3.2 Migration Flows in South America by Decade, 1960-2000**

**Figure 3.3 TERGM: Goodness-of-fit Assessment**



Except for the plot in the lower right corner, solid lines represents median of the observed networks. Box plots represents 95% confidence intervals based on 500 simulated networks.

134

### A.1.1. Pseudo-code of the Computational Model

**FIRST PROCEDURE  (Populate Model, Initialize Parameters)**

- Select and create a number of agents ($N$)
  - where $N \in [100,\infty)$ and $\{N : N \in (\mathbb{Z}^+)\}$
- Select a level of Consolidation ($C$)
  - where $C \in [0,1]$ and $\{C : C \in (R^+ \cup [0])\}$
- Select a level of Homophily Bias ($H$)
  - where $H \in [0,1]$ and $\{H : H \in (R^+ \cup [0])\}$
- Select a number of Groups or Communities ($G$)
  - where $2 \leq G \leq x$ with $\{x : x \in [3,\infty)$ and $x \in \mathbb{Z}^+\}$ and $\{G : G \in \mathbb{Z}^+\}$
- Select a number of secondary boundaries ($B$)
  - where $2 \leq B \leq n$ with $\{n : n \in [3,\infty)$ and $n \in \mathbb{Z}^+\}$ and $\{B : B \in \mathbb{Z}^+\}$.
- Select a margin of error for ($F$)
  - where $F \in [0.01,0.05]$ and $\{F : F \in (R^+ \cup [0])\}$
- Select a mean degree ($Z$)
  - where $Z \in [4,10]$ and $\{Z : Z \in (\mathbb{Z}^+)\}$
- Select a number of iterations ($Q$)
  - where $Q \in [100,\infty)$ and $\{Q : Q \in (\mathbb{Z}^+)\}$
- Select the population mean for the adoption thresholds ($T_{mean}$)
  - where $0 \leq T_{mean} \leq 1$ where $\{T_{mean} : T_{mean} \in (R^+ \cup [0])\}$
- Select the population standard deviation for the adoption thresholds ($T_{sd}$)
  - where $0 \leq T_{sd} \leq 1$ where $\{T_{sd} : T_{sd} \in (R^+ \cup [0])\}$

**SECOND PROCEDURE (Consolidation)**

- For agent i to agent $N$:
  - Randomly assign agent i to one, and only one, of the possible values of $G$ (i.e. group membership).
    - Call this distribution of agents within groups the primary boundary ($PB$)
- Create $B$ copies of $PB$
  - Induce a $C$ level of correlation between each $B$ and $PB$ by partially reshuffling the secondary boundaries
    - Stop if the average pair-wise Pearson correlation coefficient between all the boundaries is equal to $C$ +/- $F$

**THIRD PROCEDURE (Homophily Bias)**

- While $Z$ has not been reached:
  - Ask a randomly selected agent i to:

- ▪ Select a social boundary at random (any of the secondary boundaries or the **PB** can be selected). Call the selected boundary **b**
- ▪ Draw a random number **r** from the unit interval (**r** ϵ [0,1] and {**r : r** ϵ (R$^+$ U [0])}
- ▪ If-else **r ≤ H**
  - ○ Create an undirected tie with a random alter j that has the same value (i.e. group membership) in **b**
  - ○ Create an undirected tie with a random an alter j that has a different value (i.e. group membership) in **b**

## FOURTH PROCEDURE (Diffusion)

- For agent i to agent **N**:
  - Compute agent's i degree (**D$_i$**) intercultural capacity for brokerage (**IB$_i$**), and betweenness centrality (**BE$_i$**)
  - Create a variable A$_i$ to indicate if the agent has adopted the innovation. Initially, no agent is an adopter (i.e. **A$_i$** = 0)
  - Calculate cultural similarity to all other agents in the society using the simple matching coefficient (SMC), see equation 3 in Chapter 1.
  - Generate a random number (**T$_i$**), where **T$_i$** ~ N (**T$_{mean}$, T$_{sd}$**)
- Rank-order agents based on **D$_i$, IB$_i$**, and **BE$_i$**. There is one unique ranking per measure.
- Select one of four rules to pick the seed agent: IB, degree, betweenness. or random
- Based on the previous step, select the agent with highest **D$_i$** or **IB$_i$** or **BE$_i$** or select an agent at random. Call the selected agent **seed.**
- Ask agent **seed** and all her immediate neighbors to become adopters (i.e. **A$_i$** = 1). Call this set the seed neighborhood (**s**)
- Repeat **Q** times:
  - Ask a randomly selected non-adopter (i.e. **A$_i$** = 0) agent i to:
    - ▪ Randomly select one of her neighbors j
    - ▪ Adopt the innovation (i.e. **A$_i$** = 1) if j has already adopted the innovation (i.e. **A$_j$** = 1) and the similarity to agent j (i.e. SMC$_{ij}$) is ≥ **T$_i$**

## FIFTH PROCEDURE (Compute Dependent Variables)

- Compute the following quantities:
- **A$_{overall}$** $\quad = \quad$ $\dfrac{\sum_i^{N_{ns}} A_i}{N_{ns}}$
- **A$_{in}$** $\quad = \quad$ $\dfrac{\sum_i^{N_{ns}} A_i\, G_{i,seed}}{\sum_i^{N_{ns}} G_{i,seed}}$
- **A$_{out}$** $\quad = \quad$ $\dfrac{\sum_i^{N_{ns}} A_i\, |G_{i,seed} - 1)\,|}{\sum_i^{N_{ns}} |G_{i,seed} - 1)\,|}$

Where **N$_{ns}$** is the set of all agents that are not part of the seed neighborhood, and **G$_{i,seed}$** = 1 if the i$^{th}$ agent has the same group membership in the primary boundary that the seed agent, and 0 otherwise.

**Segregation along the Primary Boundary with G = 5**

**Modularity**

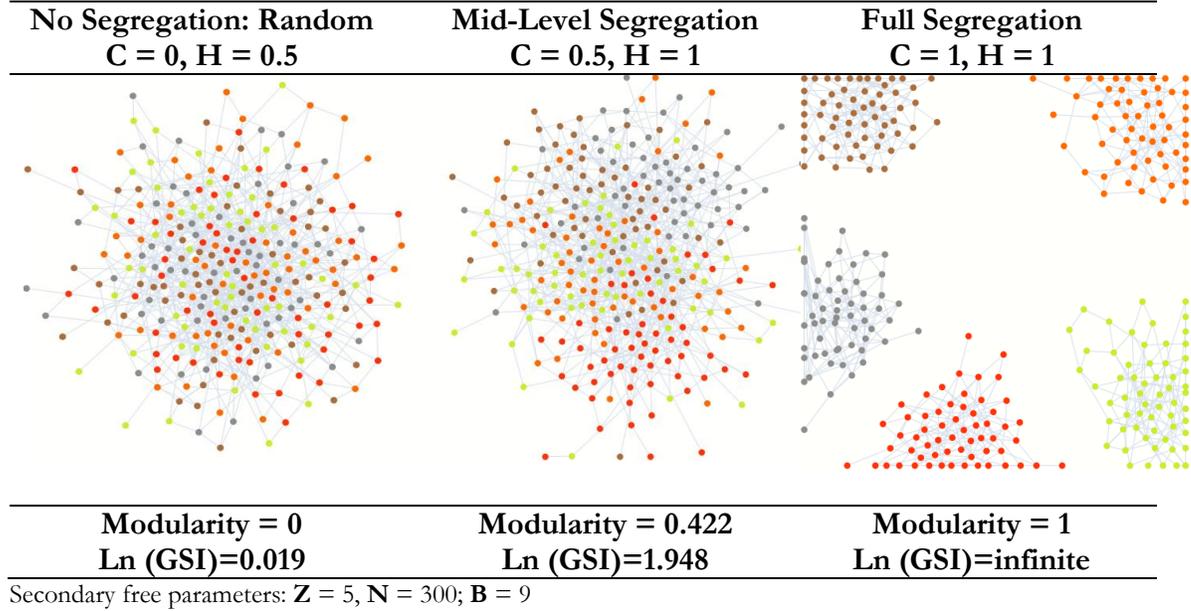|  |  | **CONSOLIDATION (C)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| **H** | 0 | -0.024 | -0.036 | -0.050 | -0.068 | -0.086 | -0.102 | -0.120 | -0.140 | -0.159 | -0.179 | -0.200 |
| **O** | 0.1 | -0.015 | -0.020 | -0.027 | -0.034 | -0.043 | -0.052 | -0.059 | -0.070 | -0.080 | -0.090 | -0.099 |
| **M** | 0.2 | -0.004 | -0.003 | -0.003 | -0.001 | -0.003 | -0.003 | -0.001 | -0.001 | 0.000 | 0.000 | 0.000 |
| **O** | 0.3 | 0.009 | 0.015 | 0.022 | 0.029 | 0.037 | 0.047 | 0.058 | 0.066 | 0.077 | 0.086 | 0.098 |
| **P** | 0.4 | 0.019 | 0.033 | 0.048 | 0.061 | 0.082 | 0.097 | 0.114 | 0.136 | 0.153 | 0.175 | 0.198 |
| **H** | 0.5 | 0.030 | 0.046 | 0.071 | 0.096 | 0.123 | 0.148 | 0.175 | 0.205 | 0.232 | 0.263 | 0.294 |
| **I** | 0.6 | 0.041 | 0.063 | 0.096 | 0.127 | 0.165 | 0.199 | 0.236 | 0.273 | 0.314 | 0.351 | 0.395 |
| **L** | 0.7 | 0.052 | 0.081 | 0.121 | 0.162 | 0.204 | 0.248 | 0.295 | 0.340 | 0.388 | 0.438 | 0.493 |
| **Y** | 0.8 | 0.061 | 0.099 | 0.143 | 0.192 | 0.246 | 0.299 | 0.355 | 0.406 | 0.470 | 0.529 | 0.594 |
|  | 0.9 | 0.073 | 0.114 | 0.167 | 0.225 | 0.287 | 0.350 | 0.411 | 0.481 | 0.546 | 0.617 | 0.696 |
| **(H)** | 1 | 0.084 | 0.134 | 0.194 | 0.260 | 0.329 | 0.403 | 0.473 | 0.546 | 0.628 | 0.710 | 0.799 |

Secondary free parameters: **Z** = 5; **N** = 300; **B** = 9; **G** = 5. Cell values averaged over 100 independent realizations.

**Ln(Gross Segregation Index)**

|  |  | **CONSOLIDATION (C)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| **H** | 0 | -0.145 | -0.234 | -0.337 | -0.487 | -0.656 | -0.832 | -1.061 | -1.359 | -1.774 | -2.462 | ∞ |
| **O** | 0.1 | -0.077 | -0.116 | -0.162 | -0.212 | -0.281 | -0.353 | -0.409 | -0.505 | -0.600 | -0.697 | -0.797 |
| **M** | 0.2 | -0.005 | -0.004 | -0.001 | 0.013 | 0.001 | -0.003 | 0.010 | 0.010 | 0.015 | 0.016 | 0.017 |
| **O** | 0.3 | 0.073 | 0.112 | 0.153 | 0.194 | 0.241 | 0.293 | 0.356 | 0.395 | 0.451 | 0.499 | 0.558 |
| **P** | 0.4 | 0.134 | 0.216 | 0.303 | 0.372 | 0.478 | 0.555 | 0.637 | 0.740 | 0.817 | 0.912 | 1.012 |
| **H** | 0.5 | 0.200 | 0.290 | 0.424 | 0.550 | 0.676 | 0.792 | 0.915 | 1.042 | 1.157 | 1.284 | 1.415 |
| **I** | 0.6 | 0.263 | 0.379 | 0.550 | 0.699 | 0.867 | 1.019 | 1.172 | 1.327 | 1.495 | 1.650 | 1.834 |
| **L** | 0.7 | 0.325 | 0.472 | 0.670 | 0.856 | 1.040 | 1.225 | 1.419 | 1.605 | 1.805 | 2.020 | 2.277 |
| **Y** | 0.8 | 0.369 | 0.562 | 0.770 | 0.988 | 1.215 | 1.436 | 1.665 | 1.882 | 2.166 | 2.458 | 2.825 |
|  | 0.9 | 0.432 | 0.637 | 0.879 | 1.129 | 1.387 | 1.647 | 1.905 | 2.220 | 2.549 | 2.980 | 3.643 |
| **(H)** | 1 | 0.488 | 0.727 | 0.996 | 1.275 | 1.559 | 1.868 | 2.183 | 2.546 | 3.058 | 3.818 | ∞ |

Secondary free parameters: **Z** = 5; **N** = 300; **B** = 9; **G** = 5. Cell values averaged over 100 independent realizations.

**Sociograms**

| No Segregation: Random<br>C = 0, H = 0.5 | Mid-Level Segregation<br>C = 0.5, H = 1 | Full Segregation<br>C = 1, H = 1 |
|:---:|:---:|:---:|
|  |  |  |
| **Modularity = 0**<br>**Ln (GSI)=0.019** | **Modularity = 0.422**<br>**Ln (GSI)=1.948** | **Modularity = 1**<br>**Ln (GSI)=infinite** |

Secondary free parameters: $\mathbf{Z}$ = 5, $\mathbf{N}$ = 300; $\mathbf{B}$ = 9

# APPENDIX A.1.3
## Segregation along the Primary Boundary with G = 10

**Modularity**

### CONSOLIDATION (C)

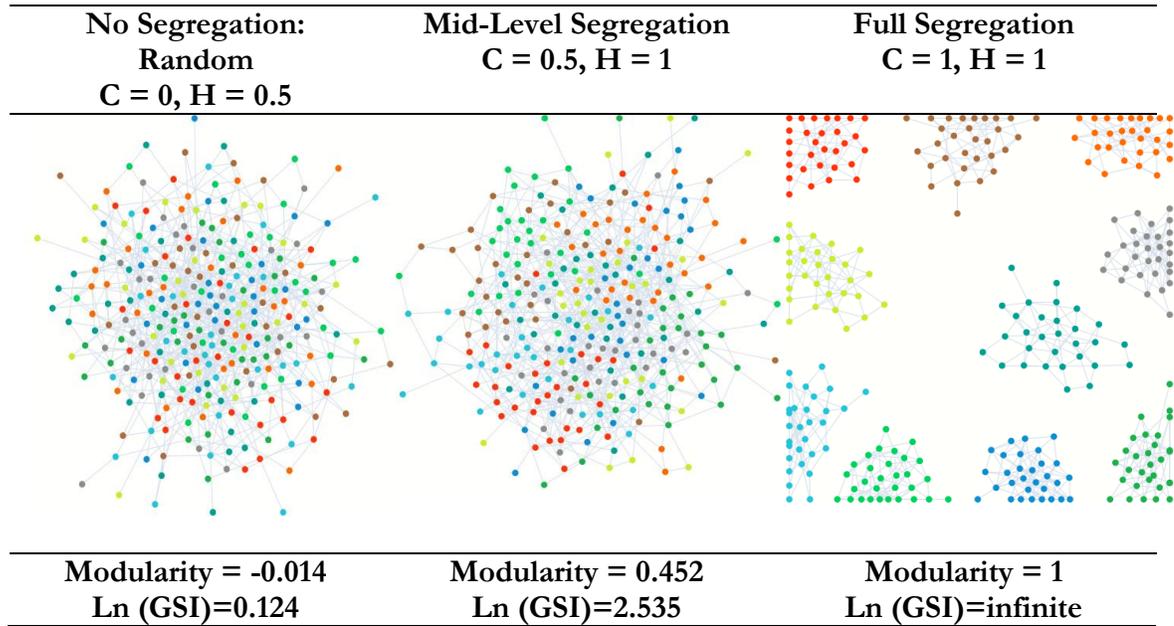|   |   | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|---|
| **H** | 0 | -0.014 | -0.020 | -0.026 | -0.035 | -0.044 | -0.052 | -0.061 | -0.069 | -0.079 | -0.089 | -0.100 |
| **O** | 0.1 | -0.002 | -0.004 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 | -0.002 | -0.001 | -0.001 | -0.001 |
| **M** | 0.2 | 0.009 | 0.012 | 0.019 | 0.031 | 0.038 | 0.050 | 0.055 | 0.068 | 0.078 | 0.087 | 0.099 |
| **O** | 0.3 | 0.018 | 0.028 | 0.047 | 0.062 | 0.083 | 0.096 | 0.113 | 0.133 | 0.152 | 0.174 | 0.195 |
| **P** | 0.4 | 0.029 | 0.049 | 0.071 | 0.097 | 0.120 | 0.143 | 0.173 | 0.203 | 0.231 | 0.258 | 0.290 |
| **H** | 0.5 | 0.041 | 0.064 | 0.095 | 0.127 | 0.158 | 0.192 | 0.231 | 0.265 | 0.309 | 0.345 | 0.386 |
| **I** | 0.6 | 0.053 | 0.080 | 0.120 | 0.160 | 0.203 | 0.246 | 0.292 | 0.337 | 0.382 | 0.434 | 0.488 |
| **L** | 0.7 | 0.062 | 0.096 | 0.142 | 0.192 | 0.246 | 0.295 | 0.349 | 0.404 | 0.463 | 0.519 | 0.587 |
| **Y** | 0.8 | 0.074 | 0.114 | 0.167 | 0.222 | 0.281 | 0.342 | 0.407 | 0.471 | 0.539 | 0.609 | 0.693 |
|   | 0.9 | 0.084 | 0.133 | 0.194 | 0.258 | 0.323 | 0.392 | 0.466 | 0.540 | 0.619 | 0.697 | 0.792 |
| **(H)** | 1 | 0.097 | 0.148 | 0.215 | 0.291 | 0.365 | 0.443 | 0.522 | 0.611 | 0.696 | 0.792 | 0.899 |

Secondary free parameters: **Z** = 5; **N** = 300; **B** = 9. Cell values averaged over 100 independent realizations.

**Ln(Gross Segregation Index)**

### CONSOLIDATION (C)

|   |   | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|---|
| **H** | 0 | -0.141 | -0.213 | -0.299 | -0.444 | -0.600 | -0.762 | -0.987 | -1.217 | -1.641 | -2.325 | ∞ |
| **O** | 0.1 | 0.009 | -0.006 | 0.004 | 0.001 | 0.006 | 0.007 | 0.004 | 0.015 | 0.021 | 0.022 | 0.020 |
| **M** | 0.2 | 0.129 | 0.167 | 0.236 | 0.348 | 0.410 | 0.509 | 0.544 | 0.648 | 0.719 | 0.779 | 0.862 |
| **O** | 0.3 | 0.223 | 0.319 | 0.486 | 0.601 | 0.753 | 0.840 | 0.949 | 1.067 | 1.176 | 1.295 | 1.404 |
| **P** | 0.4 | 0.327 | 0.499 | 0.671 | 0.847 | 0.991 | 1.127 | 1.287 | 1.440 | 1.576 | 1.701 | 1.843 |
| **H** | 0.5 | 0.436 | 0.614 | 0.836 | 1.032 | 1.211 | 1.385 | 1.574 | 1.734 | 1.929 | 2.083 | 2.256 |
| **I** | 0.6 | 0.534 | 0.732 | 0.988 | 1.218 | 1.442 | 1.648 | 1.851 | 2.049 | 2.239 | 2.458 | 2.689 |
| **L** | 0.7 | 0.603 | 0.841 | 1.121 | 1.386 | 1.645 | 1.867 | 2.100 | 2.332 | 2.584 | 2.826 | 3.144 |
| **Y** | 0.8 | 0.689 | 0.952 | 1.258 | 1.531 | 1.803 | 2.072 | 2.343 | 2.618 | 2.915 | 3.251 | 3.728 |
|   | 0.9 | 0.760 | 1.067 | 1.396 | 1.700 | 1.990 | 2.282 | 2.597 | 2.924 | 3.305 | 3.752 | 4.518 |
| **(H)** | 1 | 0.849 | 1.154 | 1.500 | 1.850 | 2.168 | 2.497 | 2.840 | 3.264 | 3.747 | 4.528 | ∞ |

Secondary free parameters: **Z** = 5; **N** = 300; **B** = 9. Cell values averaged over 100 independent realizations.

**Sociograms**

| No Segregation:<br>Random<br>C = 0, H = 0.5 | Mid-Level Segregation<br>C = 0.5, H = 1 | Full Segregation<br>C = 1, H = 1 |
|:---:|:---:|:---:|
|  |  |  |
| Modularity = -0.014<br>Ln (GSI)=0.124 | Modularity = 0.452<br>Ln (GSI)=2.535 | Modularity = 1<br>Ln (GSI)=infinite |

## Segregation along the Primary Boundary with Z = 10

**Modularity**

|  |  | **CONSOLIDATION (C)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| **H** | 0 | -0.053 | -0.080 | -0.121 | -0.164 | -0.209 | -0.255 | -0.300 | -0.345 | -0.397 | -0.448 | -0.500 |
| **O** | 0.1 | -0.043 | -0.063 | -0.096 | -0.133 | -0.168 | -0.204 | -0.240 | -0.279 | -0.314 | -0.354 | -0.398 |
| **M** | 0.2 | -0.032 | -0.048 | -0.072 | -0.100 | -0.128 | -0.150 | -0.179 | -0.206 | -0.234 | -0.266 | -0.297 |
| **O** | 0.3 | -0.025 | -0.034 | -0.049 | -0.068 | -0.083 | -0.102 | -0.117 | -0.138 | -0.156 | -0.177 | -0.197 |
| **P** | 0.4 | -0.011 | -0.018 | -0.022 | -0.034 | -0.044 | -0.054 | -0.059 | -0.071 | -0.080 | -0.088 | -0.098 |
| **H** | 0.5 | -0.002 | -0.001 | -0.002 | -0.001 | -0.001 | -0.001 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 |
| **I** | 0.6 | 0.009 | 0.013 | 0.023 | 0.033 | 0.039 | 0.048 | 0.059 | 0.068 | 0.077 | 0.088 | 0.098 |
| **L** | 0.7 | 0.019 | 0.029 | 0.046 | 0.063 | 0.083 | 0.100 | 0.119 | 0.138 | 0.157 | 0.176 | 0.193 |
| **Y** | 0.8 | 0.029 | 0.044 | 0.068 | 0.097 | 0.124 | 0.151 | 0.180 | 0.205 | 0.234 | 0.263 | 0.296 |
|  | 0.9 | 0.041 | 0.060 | 0.095 | 0.128 | 0.164 | 0.203 | 0.242 | 0.274 | 0.313 | 0.356 | 0.397 |
| **(H)** | 1 | 0.054 | 0.075 | 0.116 | 0.163 | 0.205 | 0.254 | 0.298 | 0.347 | 0.393 | 0.446 | 0.500 |

Secondary free parameters: **N** = 300; **B** = 9; **G**=2 Cell values averaged over 100 independent realizations.

**Ln(Gross Segregation Index)**

|  |  | **CONSOLIDATION (C)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| **H** | 0 | -0.213 | -0.326 | -0.502 | -0.695 | -0.914 | -1.155 | -1.424 | -1.744 | -2.222 | -2.974 | ∞ |
| **O** | 0.1 | -0.171 | -0.254 | -0.396 | -0.558 | -0.718 | -0.889 | -1.072 | -1.292 | -1.517 | -1.808 | -2.224 |
| **M** | 0.2 | -0.127 | -0.191 | -0.292 | -0.411 | -0.535 | -0.634 | -0.765 | -0.900 | -1.040 | -1.218 | -1.402 |
| **O** | 0.3 | -0.095 | -0.134 | -0.196 | -0.276 | -0.337 | -0.422 | -0.486 | -0.579 | -0.662 | -0.757 | -0.852 |
| **P** | 0.4 | -0.036 | -0.068 | -0.084 | -0.134 | -0.176 | -0.215 | -0.238 | -0.289 | -0.325 | -0.359 | -0.404 |
| **H** | 0.5 | -0.001 | 0.005 | 0.000 | 0.005 | 0.003 | 0.003 | 0.006 | 0.010 | 0.008 | 0.013 | 0.008 |
| **I** | 0.6 | 0.045 | 0.060 | 0.103 | 0.144 | 0.170 | 0.209 | 0.254 | 0.291 | 0.331 | 0.375 | 0.421 |
| **L** | 0.7 | 0.087 | 0.130 | 0.199 | 0.271 | 0.353 | 0.426 | 0.509 | 0.593 | 0.682 | 0.768 | 0.852 |
| **Y** | 0.8 | 0.130 | 0.192 | 0.293 | 0.413 | 0.530 | 0.652 | 0.785 | 0.911 | 1.057 | 1.218 | 1.411 |
|  | 0.9 | 0.177 | 0.257 | 0.406 | 0.547 | 0.711 | 0.896 | 1.100 | 1.277 | 1.521 | 1.840 | 2.234 |
| **(H)** | 1 | 0.231 | 0.322 | 0.499 | 0.706 | 0.908 | 1.164 | 1.426 | 1.773 | 2.193 | 2.958 | ∞ |

Secondary free parameters: **N** = 300; **B** = 9; **G**=2. Cell values averaged over 100 independent realizations.

### Segregation along the Primary Boundary for B = 4

## Modularity

### CONSOLIDATION (C)

| | | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **H** | 0 | -0.103 | -0.113 | -0.152 | -0.192 | -0.234 | -0.278 | -0.321 | -0.365 | -0.406 | -0.454 | -0.500 |
| **O** | 0.1 | -0.082 | -0.091 | -0.122 | -0.152 | -0.187 | -0.222 | -0.257 | -0.291 | -0.326 | -0.361 | -0.399 |
| **M** | 0.2 | -0.064 | -0.070 | -0.090 | -0.116 | -0.141 | -0.167 | -0.192 | -0.218 | -0.243 | -0.269 | -0.298 |
| **O** | 0.3 | -0.043 | -0.045 | -0.062 | -0.078 | -0.094 | -0.111 | -0.127 | -0.145 | -0.163 | -0.180 | -0.199 |
| **P** | 0.4 | -0.024 | -0.024 | -0.031 | -0.038 | -0.048 | -0.054 | -0.064 | -0.073 | -0.083 | -0.092 | -0.099 |
| **H** | 0.5 | -0.004 | -0.001 | -0.002 | 0.000 | 0.000 | 0.001 | -0.004 | 0.000 | 0.001 | 0.000 | 0.000 |
| **I** | 0.6 | 0.022 | 0.019 | 0.029 | 0.038 | 0.044 | 0.053 | 0.061 | 0.072 | 0.081 | 0.091 | 0.099 |
| **L** | 0.7 | 0.041 | 0.044 | 0.057 | 0.072 | 0.092 | 0.109 | 0.125 | 0.145 | 0.160 | 0.177 | 0.198 |
| **Y** | 0.8 | 0.060 | 0.066 | 0.087 | 0.114 | 0.138 | 0.165 | 0.193 | 0.214 | 0.243 | 0.270 | 0.297 |
| | 0.9 | 0.079 | 0.087 | 0.116 | 0.150 | 0.185 | 0.221 | 0.256 | 0.289 | 0.323 | 0.361 | 0.399 |
| **(H)** | 1 | 0.099 | 0.114 | 0.146 | 0.192 | 0.233 | 0.274 | 0.319 | 0.361 | 0.406 | 0.451 | 0.499 |

Secondary free parameters: **Z** = 5, **N** = 300; **G**=2 Cell values averaged over 100 independent realizations.

## Ln(Gross Segregation Index)

### CONSOLIDATION (C)

| | | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **H** | 0 | -0.419 | -0.463 | -0.630 | -0.816 | -1.026 | -1.271 | -1.538 | -1.881 | -2.297 | -3.088 | ∞ |
| **O** | 0.1 | -0.330 | -0.367 | -0.498 | -0.633 | -0.794 | -0.965 | -1.146 | -1.343 | -1.575 | -1.846 | -2.208 |
| **M** | 0.2 | -0.253 | -0.281 | -0.362 | -0.473 | -0.582 | -0.702 | -0.817 | -0.944 | -1.070 | -1.216 | -1.390 |
| **O** | 0.3 | -0.169 | -0.177 | -0.247 | -0.313 | -0.378 | -0.453 | -0.519 | -0.600 | -0.679 | -0.760 | -0.850 |
| **P** | 0.4 | -0.090 | -0.090 | -0.118 | -0.147 | -0.190 | -0.211 | -0.255 | -0.291 | -0.333 | -0.369 | -0.400 |
| **H** | 0.5 | -0.007 | 0.003 | 0.001 | 0.009 | 0.009 | 0.014 | -0.007 | 0.006 | 0.012 | 0.008 | 0.009 |
| **I** | 0.6 | 0.098 | 0.088 | 0.126 | 0.162 | 0.188 | 0.223 | 0.259 | 0.305 | 0.340 | 0.381 | 0.415 |
| **L** | 0.7 | 0.177 | 0.190 | 0.240 | 0.304 | 0.388 | 0.460 | 0.526 | 0.615 | 0.682 | 0.763 | 0.861 |
| **Y** | 0.8 | 0.254 | 0.278 | 0.367 | 0.479 | 0.587 | 0.708 | 0.836 | 0.942 | 1.088 | 1.238 | 1.403 |
| | 0.9 | 0.335 | 0.368 | 0.491 | 0.636 | 0.802 | 0.974 | 1.158 | 1.353 | 1.578 | 1.864 | 2.227 |
| **(H)** | 1 | 0.416 | 0.481 | 0.621 | 0.832 | 1.036 | 1.261 | 1.547 | 1.869 | 2.319 | 3.047 | ∞ |

Secondary free parameters: **Z** = 5, **N** = 300; **G**=2. Cell values averaged over 100 independent realizations.

# APPENDIX A.1.6
## Segregation along the Primary Boundary with N = 500

**Modularity**

|  |  | **CONSOLIDATION (C)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| **H** | 0 | -0.053 | -0.077 | -0.120 | -0.165 | -0.212 | -0.257 | -0.304 | -0.350 | -0.398 | -0.447 | -0.500 |
| **O** | 0.1 | -0.045 | -0.062 | -0.098 | -0.135 | -0.170 | -0.207 | -0.244 | -0.279 | -0.320 | -0.356 | -0.399 |
| **M** | 0.2 | -0.033 | -0.048 | -0.073 | -0.098 | -0.128 | -0.155 | -0.184 | -0.211 | -0.239 | -0.270 | -0.299 |
| **O** | 0.3 | -0.020 | -0.031 | -0.051 | -0.067 | -0.086 | -0.107 | -0.121 | -0.139 | -0.161 | -0.180 | -0.198 |
| **P** | 0.4 | -0.014 | -0.016 | -0.027 | -0.035 | -0.045 | -0.051 | -0.063 | -0.071 | -0.079 | -0.088 | -0.102 |
| **H** | 0.5 | -0.003 | -0.002 | -0.004 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.002 | -0.002 | -0.001 |
| **I** | 0.6 | 0.009 | 0.014 | 0.024 | 0.034 | 0.042 | 0.053 | 0.060 | 0.068 | 0.080 | 0.089 | 0.100 |
| **L** | 0.7 | 0.018 | 0.030 | 0.049 | 0.065 | 0.086 | 0.104 | 0.121 | 0.140 | 0.158 | 0.181 | 0.199 |
| **Y** | 0.8 | 0.032 | 0.045 | 0.072 | 0.100 | 0.127 | 0.155 | 0.180 | 0.209 | 0.238 | 0.268 | 0.299 |
|  | 0.9 | 0.040 | 0.060 | 0.096 | 0.133 | 0.169 | 0.206 | 0.245 | 0.278 | 0.313 | 0.358 | 0.399 |
| **(H)** | 1 | 0.053 | 0.077 | 0.119 | 0.166 | 0.209 | 0.258 | 0.303 | 0.348 | 0.398 | 0.448 | 0.500 |

Secondary free parameters: **Z** = 5; **G**=2; **B**=9. Cell values averaged over 100 independent realizations.

**Ln(Gross Segregation Index)**

|  |  | **CONSOLIDATION (C)** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  |  | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
| **H** | 0 | -0.211 | -0.309 | -0.492 | -0.689 | -0.912 | -1.146 | -1.423 | -1.748 | -2.201 | -2.927 | ∞ |
| **O** | 0.1 | -0.177 | -0.248 | -0.396 | -0.555 | -0.711 | -0.883 | -1.073 | -1.270 | -1.525 | -1.799 | -2.206 |
| **M** | 0.2 | -0.130 | -0.190 | -0.291 | -0.396 | -0.523 | -0.644 | -0.775 | -0.906 | -1.046 | -1.218 | -1.391 |
| **O** | 0.3 | -0.075 | -0.122 | -0.203 | -0.267 | -0.345 | -0.437 | -0.496 | -0.572 | -0.670 | -0.756 | -0.843 |
| **P** | 0.4 | -0.050 | -0.060 | -0.104 | -0.139 | -0.178 | -0.204 | -0.253 | -0.284 | -0.318 | -0.353 | -0.415 |
| **H** | 0.5 | -0.008 | -0.002 | -0.011 | 0.002 | -0.001 | 0.000 | -0.001 | 0.001 | -0.002 | -0.001 | 0.002 |
| **I** | 0.6 | 0.040 | 0.060 | 0.101 | 0.141 | 0.176 | 0.220 | 0.247 | 0.282 | 0.333 | 0.371 | 0.415 |
| **L** | 0.7 | 0.076 | 0.128 | 0.202 | 0.270 | 0.355 | 0.430 | 0.506 | 0.588 | 0.665 | 0.774 | 0.857 |
| **Y** | 0.8 | 0.136 | 0.187 | 0.297 | 0.413 | 0.529 | 0.651 | 0.769 | 0.905 | 1.054 | 1.216 | 1.397 |
|  | 0.9 | 0.167 | 0.250 | 0.396 | 0.556 | 0.714 | 0.889 | 1.087 | 1.272 | 1.492 | 1.820 | 2.214 |
| **(H)** | 1 | 0.219 | 0.317 | 0.496 | 0.701 | 0.905 | 1.160 | 1.424 | 1.747 | 2.208 | 2.946 | ∞ |

Secondary free parameters: **Z** = 5; **G**=2; **B**=9. Cell values averaged over 100 independent realizations.

# Effectiveness of Cultural Brokerage: Baseline Model with Changes in Key Free Parameters

**Baseline Model with Threshold Mean ($T_{mean}$) = 0.4**
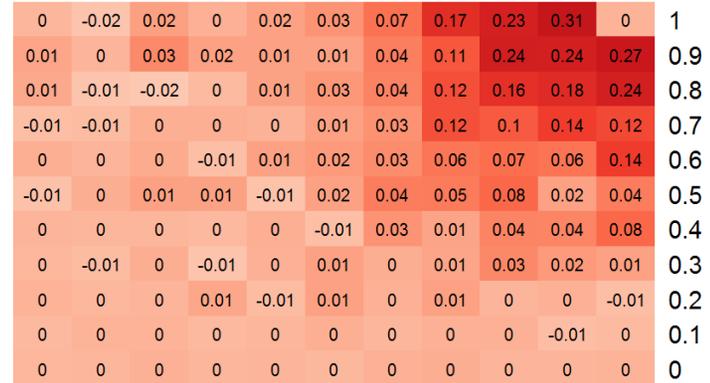


H O M O P H I L Y

C O N S O L I D A T I O N

(Cultural Brokerage) – (Random)

(Cultural Brokerage) – (Popularity)

(Culturage Brokerage) – (Structural Brokerage)

**Baseline Model:**
N=300; Z=5; G=5; B=9; Q=10000; M=0; $T_{sd}$=0.05

Adoption

# Baseline Model with Threshold Mean ($T_{mean}$) = 0.6

## H O M O P H I L Y

**CONSOLIDATION**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0.01 | 0.01 | 0.04 | 0.14 | 0.28 | 0.35 | 0.47 | 0.42 | 0.38 | 0 | 1 |
| | 0 | 0 | 0.01 | 0.03 | 0.1 | 0.26 | 0.36 | 0.43 | 0.42 | 0.49 | 0.47 | 0.9 |
| | 0 | 0 | 0.01 | 0.02 | 0.1 | 0.19 | 0.35 | 0.45 | 0.43 | 0.45 | 0.51 | 0.8 |
| | 0 | 0 | 0.01 | 0.02 | 0.08 | 0.16 | 0.37 | 0.38 | 0.46 | 0.42 | 0.47 | 0.7 |
| | 0 | 0 | 0 | 0.02 | 0.06 | 0.13 | 0.26 | 0.4 | 0.39 | 0.44 | 0.41 | 0.6 |
| | 0 | 0 | 0 | 0.02 | 0.04 | 0.1 | 0.18 | 0.31 | 0.37 | 0.4 | 0.35 | 0.5 |
| | 0 | 0 | 0 | 0.01 | 0.02 | 0.06 | 0.13 | 0.2 | 0.29 | 0.3 | 0.37 | 0.4 |
| | 0 | 0 | 0 | 0.01 | 0.02 | 0.05 | 0.07 | 0.12 | 0.14 | 0.19 | 0.22 | 0.3 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.04 | 0.05 | 0.09 | 0.07 | 0.08 | 0.2 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.03 | 0.03 | 0.02 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 |

**(Cultural Brokerage) − (Random)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | 0.01 | 0.03 | 0.08 | 0.09 | 0.15 | 0.22 | 0.29 | 0 | 1 |
| | 0 | 0 | 0 | 0.01 | -0.01 | 0.07 | 0.1 | 0.13 | 0.15 | 0.21 | 0.28 | 0.9 |
| | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.12 | 0.12 | 0.15 | 0.21 | 0.25 | 0.8 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.11 | 0.08 | 0.11 | 0.15 | 0.16 | 0.7 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.05 | 0.07 | 0.07 | 0.09 | 0.14 | 0.6 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.04 | 0.05 | 0.07 | 0.08 | 0.02 | 0.5 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0.03 | 0.05 | 0.04 | 0.08 | 0.4 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0.02 | -0.01 | -0.01 | 0.02 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | -0.01 | 0 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) − (Popularity)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.02 | 0.09 | 0.06 | -0.01 | 0 | 1 |
| | 0 | 0 | 0 | 0 | 0 | 0.05 | 0.06 | 0.08 | 0.08 | 0.05 | 0.02 | 0.9 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.07 | 0.05 | 0.06 | 0.05 | 0.09 | 0.8 |
| | 0 | 0 | 0 | 0.01 | 0 | 0.04 | 0.11 | 0.06 | 0.07 | 0.07 | 0.08 | 0.7 |
| | 0 | 0 | 0 | -0.01 | 0.01 | -0.02 | 0.01 | 0.07 | 0.05 | 0.1 | 0.07 | 0.6 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.03 | 0.07 | 0.06 | 0.06 | 0.08 | 0.5 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.06 | 0.04 | 0.07 | 0.4 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | -0.01 | 0.02 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | -0.01 | 0.01 | 0.01 | 0.01 | 0 | 0.01 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) − (Structural Brokerage)**

**Baseline Model:**
N=300; Z=5; G=5; B=9; Q=10000; M=0; $T_{sd}$=0.05

Adoption

0   0.4

145

Baseline Model with Threshold Mean ($T_{mean}$) = 0.7

H O M O P H I L Y

(Cultural Brokerage) – (Random)

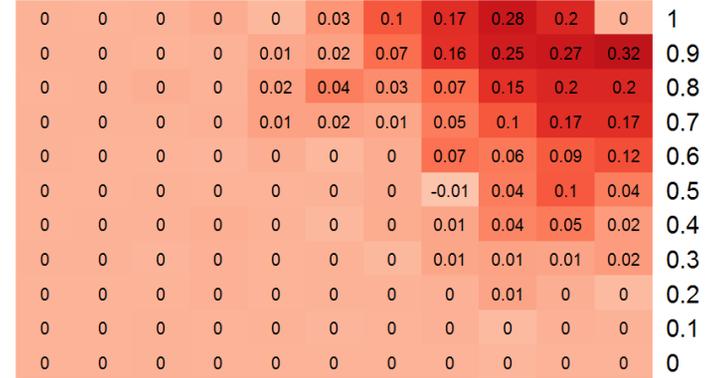(Cultural Brokerage) – (Popularity)

C O N S O L I D A T I O N

(Cultural Brokerage) – (Structural Brokerage)

**Baseline Model:**
N=300; Z=5; G=5; B=9; Q=10000; M=0; $T_{sd}$=0.05

Adoption

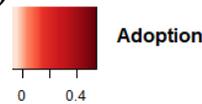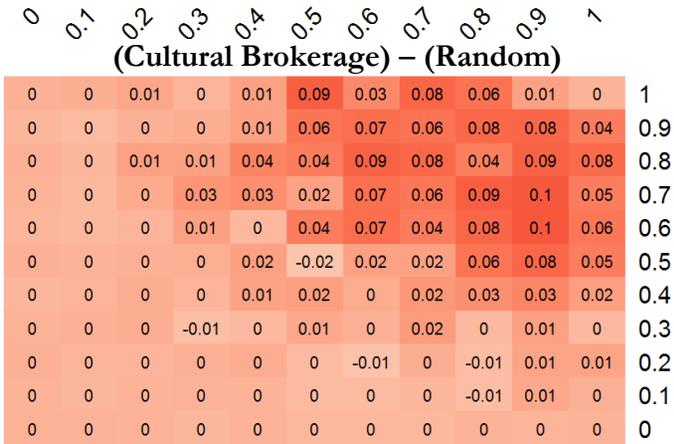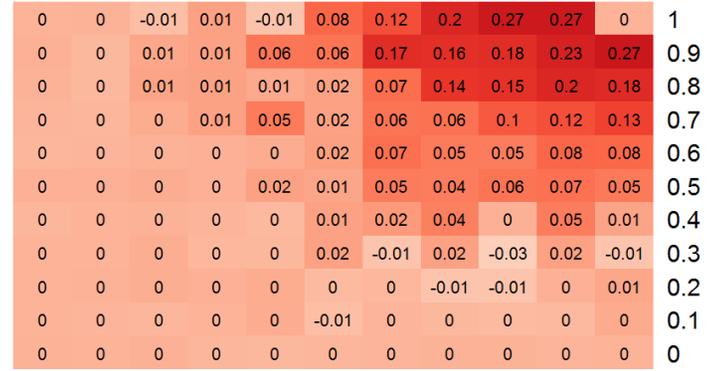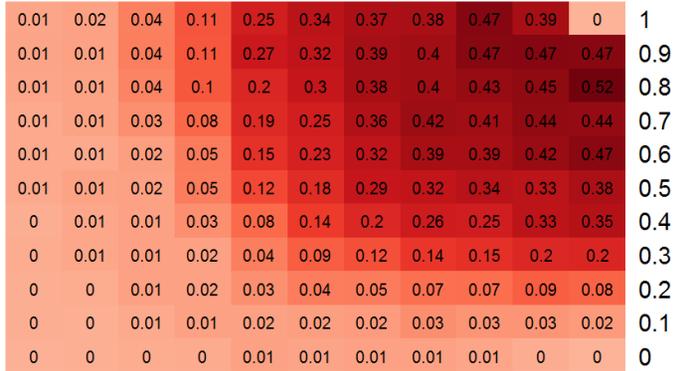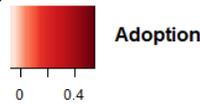**Baseline Model with Threshold Standard Deviation ($T_{sd}$) = 0.01**

## H O M O P H I L Y

**CONSOLIDATION** (vertical axis)

### (Cultural Brokerage) − (Random)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.01 | 0.02 | 0.04 | 0.11 | 0.25 | 0.34 | 0.37 | 0.38 | 0.47 | 0.39 | 0 |
| 0.9 | 0.01 | 0.01 | 0.04 | 0.11 | 0.27 | 0.32 | 0.39 | 0.4 | 0.47 | 0.47 | 0.47 |
| 0.8 | 0.01 | 0.01 | 0.04 | 0.1 | 0.2 | 0.3 | 0.38 | 0.4 | 0.43 | 0.45 | 0.52 |
| 0.7 | 0.01 | 0.01 | 0.03 | 0.08 | 0.19 | 0.25 | 0.36 | 0.42 | 0.41 | 0.44 | 0.44 |
| 0.6 | 0.01 | 0.01 | 0.02 | 0.05 | 0.15 | 0.23 | 0.32 | 0.39 | 0.39 | 0.42 | 0.47 |
| 0.5 | 0.01 | 0.01 | 0.02 | 0.05 | 0.12 | 0.18 | 0.29 | 0.32 | 0.34 | 0.33 | 0.38 |
| 0.4 | 0 | 0.01 | 0.01 | 0.03 | 0.08 | 0.14 | 0.2 | 0.26 | 0.25 | 0.33 | 0.35 |
| 0.3 | 0 | 0.01 | 0.01 | 0.02 | 0.04 | 0.09 | 0.12 | 0.14 | 0.15 | 0.2 | 0.2 |
| 0.2 | 0 | 0 | 0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.07 | 0.07 | 0.09 | 0.08 |
| 0.1 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.02 |
| 0 | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 |

### (Cultural Brokerage) − (Popularity)

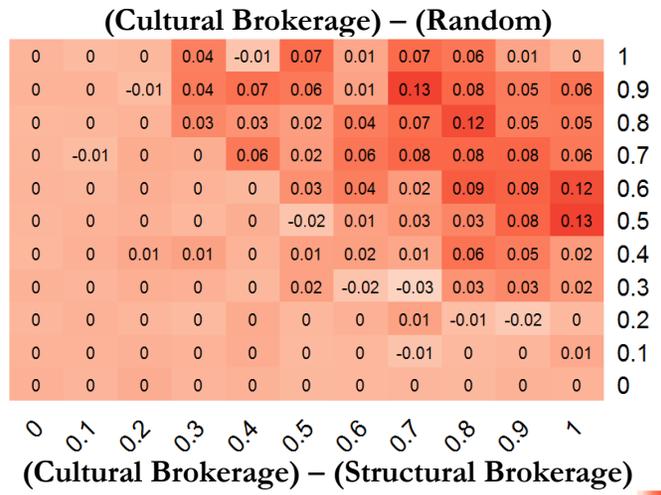| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | -0.01 | 0.01 | -0.01 | 0.08 | 0.12 | 0.2 | 0.27 | 0.27 | 0 |
| 0.9 | 0 | 0 | 0.01 | 0.01 | 0.06 | 0.06 | 0.17 | 0.16 | 0.18 | 0.23 | 0.27 |
| 0.8 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.02 | 0.07 | 0.14 | 0.15 | 0.2 | 0.18 |
| 0.7 | 0 | 0 | 0 | 0.01 | 0.05 | 0.02 | 0.06 | 0.06 | 0.1 | 0.12 | 0.13 |
| 0.6 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0.07 | 0.05 | 0.05 | 0.08 | 0.08 |
| 0.5 | 0 | 0 | 0 | 0 | 0.02 | 0.01 | 0.05 | 0.04 | 0.06 | 0.07 | 0.05 |
| 0.4 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.02 | 0.04 | 0 | 0.05 | 0.01 |
| 0.3 | 0 | 0 | 0 | 0 | 0 | 0.02 | -0.01 | 0.02 | -0.03 | 0.02 | -0.01 |
| 0.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0 | 0.01 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Cultural Brokerage) − (Structural Brokerage)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0.01 | 0 | 0.01 | 0.09 | 0.03 | 0.08 | 0.06 | 0.01 | 0 |
| 0.9 | 0 | 0 | 0 | 0 | 0.01 | 0.06 | 0.07 | 0.06 | 0.08 | 0.08 | 0.04 |
| 0.8 | 0 | 0 | 0.01 | 0.01 | 0.04 | 0.04 | 0.09 | 0.08 | 0.04 | 0.09 | 0.08 |
| 0.7 | 0 | 0 | 0 | 0.03 | 0.03 | 0.02 | 0.07 | 0.06 | 0.09 | 0.1 | 0.05 |
| 0.6 | 0 | 0 | 0 | 0.01 | 0 | 0.04 | 0.07 | 0.04 | 0.08 | 0.1 | 0.06 |
| 0.5 | 0 | 0 | 0 | 0 | 0.02 | -0.02 | 0.02 | 0.02 | 0.06 | 0.08 | 0.05 |
| 0.4 | 0 | 0 | 0 | 0 | 0.01 | 0.02 | 0 | 0.02 | 0.03 | 0.03 | 0.02 |
| 0.3 | 0 | 0 | 0 | -0.01 | 0 | 0.01 | 0 | 0.02 | 0 | 0.01 | 0 |
| 0.2 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | -0.01 | 0.01 | 0.01 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0.01 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Baseline Model:**
N=300; Z=5; G=5; B=9; Q=10000; M=0; $T_{mean}$=0.5

**Adoption**
0   0.4

# Baseline Model with Threshold Standard Deviation ($T_{sd}$) = 0.1

## H O M O P H I L Y

**CONSOLIDATION**

### (Cultural Brokerage) – (Random)

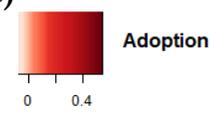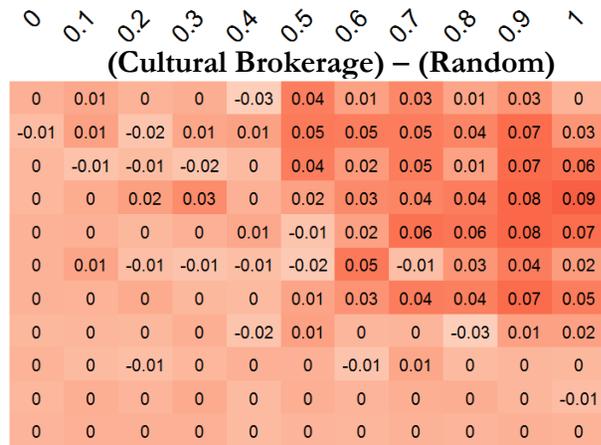| Cons\Homo | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.02 | 0.02 | 0.06 | 0.17 | 0.31 | 0.33 | 0.27 | 0.39 | 0.4 | 0.4 | 0 |
| 0.9 | 0.02 | 0.02 | 0.04 | 0.15 | 0.26 | 0.29 | 0.35 | 0.41 | 0.41 | 0.47 | 0.51 |
| 0.8 | 0.01 | 0.02 | 0.05 | 0.11 | 0.21 | 0.29 | 0.31 | 0.37 | 0.43 | 0.47 | 0.47 |
| 0.7 | 0.01 | 0.01 | 0.03 | 0.06 | 0.2 | 0.31 | 0.36 | 0.4 | 0.42 | 0.45 | 0.46 |
| 0.6 | 0.01 | 0.01 | 0.02 | 0.06 | 0.12 | 0.28 | 0.31 | 0.31 | 0.41 | 0.41 | 0.46 |
| 0.5 | 0.01 | 0.01 | 0.02 | 0.04 | 0.08 | 0.17 | 0.25 | 0.29 | 0.35 | 0.36 | 0.44 |
| 0.4 | 0.01 | 0.01 | 0.02 | 0.04 | 0.07 | 0.12 | 0.17 | 0.25 | 0.29 | 0.3 | 0.29 |
| 0.3 | 0.01 | 0.01 | 0.02 | 0.02 | 0.05 | 0.09 | 0.1 | 0.14 | 0.15 | 0.2 | 0.23 |
| 0.2 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.03 | 0.05 | 0.07 | 0.07 | 0.06 | 0.07 |
| 0.1 | 0 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.02 | 0.03 | 0.03 | 0.02 |
| 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 |

### (Cultural Brokerage) – (Popularity)

| Cons\Homo | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | -0.01 | 0.02 | 0.06 | 0.09 | 0.09 | 0.18 | 0.26 | 0.26 | 0 |
| 0.9 | 0 | 0 | 0 | 0.03 | 0.05 | 0.09 | 0.06 | 0.16 | 0.19 | 0.23 | 0.31 |
| 0.8 | 0 | 0 | 0 | 0.01 | 0.05 | 0.09 | 0.07 | 0.08 | 0.19 | 0.15 | 0.2 |
| 0.7 | 0 | 0 | -0.01 | 0.01 | 0.06 | 0.02 | 0.04 | 0.11 | 0.1 | 0.16 | 0.17 |
| 0.6 | 0 | 0 | 0 | 0 | -0.01 | 0.05 | 0.05 | 0.04 | 0.07 | 0.07 | 0.12 |
| 0.5 | 0 | 0 | 0 | 0 | -0.01 | 0.02 | 0.02 | 0.04 | 0.06 | 0.07 | 0.08 |
| 0.4 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | 0.01 | 0.03 | 0.05 | 0 |
| 0.3 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0.01 | 0.01 | 0.02 | 0.04 |
| 0.2 | 0 | 0 | 0 | 0 | -0.01 | 0 | -0.01 | 0.01 | 0 | -0.01 | -0.01 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Cultural Brokerage) – (Structural Brokerage)

| Cons\Homo | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.04 | -0.01 | 0.07 | 0.01 | 0.07 | 0.06 | 0.01 | 0 |
| 0.9 | 0 | 0 | -0.01 | 0.04 | 0.07 | 0.06 | 0.01 | 0.13 | 0.08 | 0.05 | 0.06 |
| 0.8 | 0 | 0 | 0 | 0.03 | 0.03 | 0.02 | 0.04 | 0.07 | 0.12 | 0.05 | 0.05 |
| 0.7 | 0 | -0.01 | 0 | 0 | 0.06 | 0.02 | 0.06 | 0.08 | 0.08 | 0.08 | 0.06 |
| 0.6 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.04 | 0.02 | 0.09 | 0.09 | 0.12 |
| 0.5 | 0 | 0 | 0 | 0 | 0 | -0.02 | 0.01 | 0.03 | 0.03 | 0.08 | 0.13 |
| 0.4 | 0 | 0 | 0.01 | 0.01 | 0 | 0.01 | 0.02 | 0.01 | 0.06 | 0.05 | 0.02 |
| 0.3 | 0 | 0 | 0 | 0 | 0 | 0.02 | -0.02 | -0.03 | 0.03 | 0.03 | 0.02 |
| 0.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | -0.01 | -0.02 | 0 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0 | 0.01 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Baseline Model:**
N=300; Z=5; G=5; B=9; Q=10000; M=0; $T_{mean}$=0.5

**Adoption**

0   0.4

# Baseline Model with Threshold Standard Deviation ($T_{sd}$) = 0.15

## H O M O P H I L Y

**C O N S O L I D A T I O N**

### (Cultural Brokerage) − (Random)

| Consolidation \ Homophily | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.03 | 0.04 | 0.07 | 0.18 | 0.2 | 0.23 | 0.19 | 0.31 | 0.41 | 0.42 | 0 |
| 0.9 | 0.02 | 0.04 | 0.05 | 0.12 | 0.2 | 0.24 | 0.23 | 0.33 | 0.35 | 0.45 | 0.43 |
| 0.8 | 0.03 | 0.03 | 0.05 | 0.1 | 0.21 | 0.32 | 0.22 | 0.27 | 0.35 | 0.44 | 0.49 |
| 0.7 | 0.02 | 0.03 | 0.07 | 0.12 | 0.14 | 0.26 | 0.29 | 0.26 | 0.36 | 0.42 | 0.45 |
| 0.6 | 0.02 | 0.03 | 0.03 | 0.07 | 0.13 | 0.26 | 0.32 | 0.32 | 0.41 | 0.39 | 0.43 |
| 0.5 | 0.01 | 0.03 | 0.03 | 0.05 | 0.08 | 0.14 | 0.26 | 0.3 | 0.31 | 0.27 | 0.37 |
| 0.4 | 0.02 | 0.01 | 0.04 | 0.04 | 0.07 | 0.11 | 0.2 | 0.25 | 0.29 | 0.37 | 0.3 |
| 0.3 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.08 | 0.09 | 0.13 | 0.13 | 0.2 | 0.22 |
| 0.2 | 0.01 | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.04 | 0.07 | 0.06 | 0.07 | 0.07 |
| 0.1 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.02 |
| 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 |

### (Cultural Brokerage) − (Popularity)

| Consolidation \ Homophily | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.01 | 0 | 0.01 | 0 | 0.03 | 0.04 | 0.14 | 0.24 | 0.3 | 0 |
| 0.9 | 0 | 0.01 | 0 | -0.02 | 0.02 | 0.06 | 0.07 | 0.1 | 0.15 | 0.24 | 0.29 |
| 0.8 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0.03 | 0.06 | 0.09 | 0.14 | 0.27 |
| 0.7 | -0.01 | 0.01 | 0.01 | 0.01 | 0 | 0.04 | 0.03 | 0.05 | 0.04 | 0.13 | 0.17 |
| 0.6 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.05 | 0.07 | 0.05 | 0.07 | 0.1 |
| 0.5 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0.04 | 0.01 | 0.04 | 0.02 | 0.06 |
| 0.4 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0.04 | 0.03 | 0.05 | 0.07 | 0.05 |
| 0.3 | 0 | 0 | 0 | 0 | -0.01 | 0.02 | -0.01 | -0.02 | 0.01 | 0.02 | 0.02 |
| 0.2 | -0.01 | 0 | -0.01 | 0 | 0 | 0.01 | 0 | 0 | 0 | 0 | -0.01 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Cultural Brokerage) − (Structural Brokerage)

| Consolidation \ Homophily | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.01 | 0 | 0 | -0.03 | 0.04 | 0.01 | 0.03 | 0.01 | 0.03 | 0 |
| 0.9 | -0.01 | 0.01 | -0.02 | 0.01 | 0.01 | 0.05 | 0.05 | 0.05 | 0.04 | 0.07 | 0.03 |
| 0.8 | 0 | -0.01 | -0.01 | -0.02 | 0 | 0.04 | 0.02 | 0.05 | 0.01 | 0.07 | 0.06 |
| 0.7 | 0 | 0 | 0.02 | 0.03 | 0 | 0.02 | 0.03 | 0.04 | 0.04 | 0.08 | 0.09 |
| 0.6 | 0 | 0 | 0 | 0 | 0.01 | -0.01 | 0.02 | 0.06 | 0.06 | 0.08 | 0.07 |
| 0.5 | 0 | 0.01 | -0.01 | -0.01 | -0.01 | -0.02 | 0.05 | -0.01 | 0.03 | 0.04 | 0.02 |
| 0.4 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.04 | 0.04 | 0.07 | 0.05 |
| 0.3 | 0 | 0 | 0 | 0 | -0.02 | 0.01 | 0 | 0 | -0.03 | 0.01 | 0.02 |
| 0.2 | 0 | 0 | -0.01 | 0 | 0 | 0 | -0.01 | 0.01 | 0 | 0 | 0 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Baseline Model:**
N=300; Z=5; G=5; B=9; Q=10000; M=0; $T_{mean}$=0.5

**Adoption**

0    0.4

# Baseline Model with Number of Groups (G) = 3

## H O M O P H I L Y

**CONSOLIDATION**

### (Cultural Brokerage) − (Random)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.17 | 0.21 | 0.15 | 0.06 | 0.03 | 0.06 | 0.14 | 0.34 | 0.57 | 0.65 | 0 | 1 |
| | 0.12 | 0.18 | 0.22 | 0.1 | 0.03 | 0.03 | 0.17 | 0.39 | 0.52 | 0.54 | 0.67 | 0.9 |
| | 0.13 | 0.15 | 0.16 | 0.19 | 0.09 | 0.09 | 0.18 | 0.23 | 0.45 | 0.52 | 0.57 | 0.8 |
| | 0.1 | 0.11 | 0.17 | 0.19 | 0.14 | 0.1 | 0.13 | 0.24 | 0.31 | 0.42 | 0.44 | 0.7 |
| | 0.06 | 0.1 | 0.18 | 0.23 | 0.19 | 0.13 | 0.17 | 0.22 | 0.33 | 0.33 | 0.37 | 0.6 |
| | 0.07 | 0.07 | 0.13 | 0.2 | 0.26 | 0.2 | 0.18 | 0.24 | 0.29 | 0.22 | 0.28 | 0.5 |
| | 0.05 | 0.06 | 0.1 | 0.13 | 0.2 | 0.24 | 0.25 | 0.27 | 0.23 | 0.24 | 0.24 | 0.4 |
| | 0.04 | 0.04 | 0.09 | 0.12 | 0.17 | 0.2 | 0.24 | 0.23 | 0.26 | 0.2 | 0.22 | 0.3 |
| | 0.03 | 0.03 | 0.07 | 0.07 | 0.1 | 0.12 | 0.14 | 0.14 | 0.11 | 0.1 | 0.09 | 0.2 |
| | 0.03 | 0.02 | 0.04 | 0.05 | 0.05 | 0.05 | 0.08 | 0.06 | 0.03 | 0.03 | 0.02 | 0.1 |
| | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 | 0.03 | 0.02 | 0.01 | 0 | 0 |

### (Cultural Brokerage) − (Popularity)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.07 | 0.22 | 0 | 1 |
| | -0.01 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0.12 | 0.2 | 0.31 | 0.9 |
| | 0.01 | 0 | 0 | 0 | 0.01 | 0 | 0 | 0.01 | 0.03 | 0.19 | 0.19 | 0.8 |
| | 0 | 0.01 | 0 | 0 | -0.01 | 0 | 0 | 0 | 0.04 | 0.09 | 0.11 | 0.7 |
| | 0.01 | 0.01 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0.03 | 0.04 | 0.12 | 0.6 |
| | 0.02 | 0.01 | 0.01 | 0.01 | -0.01 | 0 | 0.03 | 0.02 | 0.03 | 0.07 | 0.07 | 0.5 |
| | 0.01 | -0.03 | 0 | -0.01 | 0 | 0.01 | -0.02 | 0.01 | 0.04 | 0.05 | 0.06 | 0.4 |
| | 0 | 0.01 | 0.02 | 0.02 | -0.01 | 0 | -0.02 | 0.03 | 0.03 | 0.01 | -0.01 | 0.3 |
| | 0 | 0.01 | 0.01 | 0.01 | -0.01 | -0.01 | 0.03 | 0 | -0.01 | -0.01 | -0.01 | 0.2 |
| | 0 | -0.01 | 0.01 | -0.02 | 0.01 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 |
| | 0 | -0.01 | -0.01 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Cultural Brokerage) − (Structural Brokerage)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0.02 | 0 | 0 | 0.01 | 0 | 0.02 | 0.07 | 0.1 | 0 | 0 | 1 |
| | -0.01 | 0.04 | 0 | 0 | 0 | 0.02 | 0.01 | 0.09 | 0.05 | 0.08 | 0.11 | 0.9 |
| | 0.01 | 0 | 0 | 0.01 | 0.02 | 0.01 | 0.02 | 0.06 | 0.07 | 0.1 | 0.12 | 0.8 |
| | -0.01 | 0 | 0 | 0.01 | 0 | -0.01 | 0.01 | 0.05 | 0.04 | 0.06 | 0.12 | 0.7 |
| | -0.02 | -0.02 | 0.03 | 0.02 | -0.02 | 0 | 0.02 | 0.02 | 0.04 | 0.05 | 0.02 | 0.6 |
| | 0.01 | 0 | 0.01 | 0 | 0.03 | 0.01 | 0.01 | 0.04 | 0.01 | 0.01 | 0.04 | 0.5 |
| | 0 | -0.01 | -0.01 | -0.01 | -0.01 | -0.01 | 0.02 | 0.04 | 0.01 | 0.01 | 0.01 | 0.4 |
| | 0 | 0 | -0.01 | 0.01 | 0.03 | 0.02 | 0.03 | 0.03 | 0 | -0.02 | 0 | 0.3 |
| | 0 | 0 | 0.02 | -0.02 | 0.01 | -0.02 | -0.01 | -0.01 | -0.01 | 0 | 0 | 0.2 |
| | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0 | 0.01 | -0.01 | -0.01 | 0 | 0.1 |
| | 0 | 0 | -0.01 | 0.01 | 0 | -0.01 | 0 | 0 | 0 | 0 | 0 | 0 |

**Baseline Model:**
N=300; Z=5; B=9; Q=10000; M=0; $T_{mean}$=0.5; $T_{mean}$=0.05

**Adoption**

0    0.4

150

Baseline Model with Number of Groups (G) = 10

**H O M O P H I L Y**

(Cultural Brokerage) − (Random)

(Cultural Brokerage) − (Popularity)
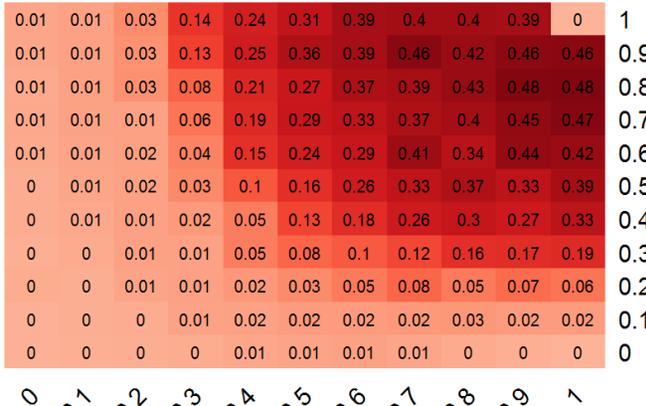
(Cultural Brokerage) − (Structural Brokerage)

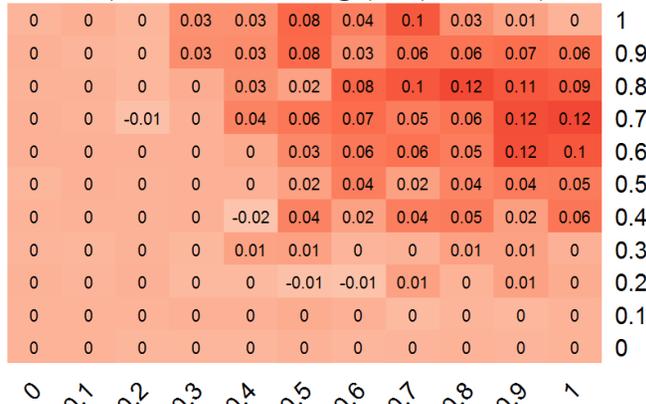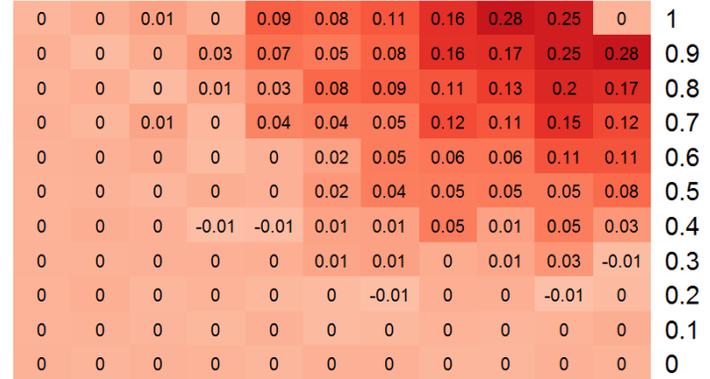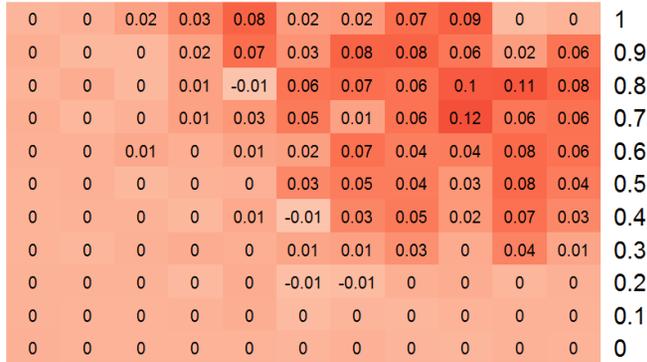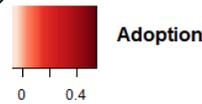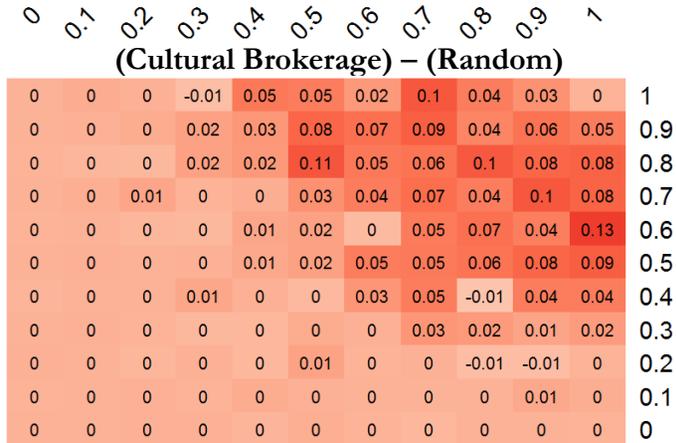**Baseline Model:**
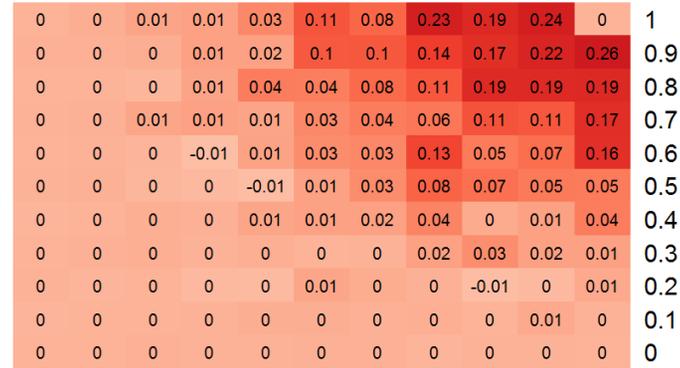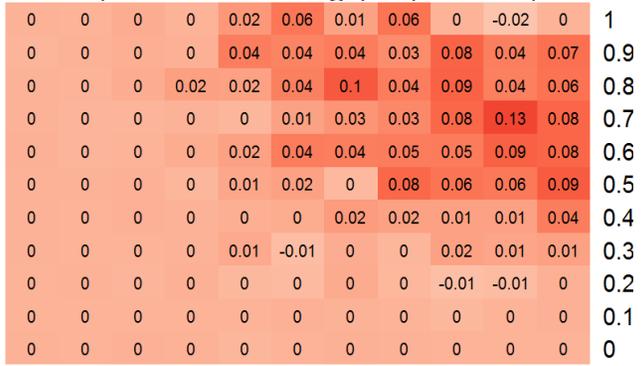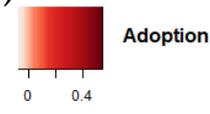N=300; Z=5; B=9; Q=10000; M=0; $T_{mean}$=0.5; $T_{mean}$=0.05

Adoption

151

# Baseline Model with Number of Secondary Boundaries (B) = 4

## H  O  M  O  P  H  I  L  Y

**C O N S O L I D A T I O N**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.07 | 0.08 | 0.18 | 0.17 | 0.2 | 0.15 | 0.23 | 0.34 | 0.36 | 0.37 | 0 | 1 |
| | 0.05 | 0.08 | 0.19 | 0.25 | 0.27 | 0.17 | 0.23 | 0.36 | 0.38 | 0.47 | 0.47 | 0.9 |
| | 0.05 | 0.06 | 0.1 | 0.17 | 0.25 | 0.23 | 0.33 | 0.31 | 0.44 | 0.42 | 0.48 | 0.8 |
| | 0.03 | 0.05 | 0.09 | 0.18 | 0.27 | 0.29 | 0.28 | 0.29 | 0.43 | 0.44 | 0.44 | 0.7 |
| | 0.03 | 0.04 | 0.06 | 0.13 | 0.2 | 0.27 | 0.31 | 0.31 | 0.39 | 0.4 | 0.39 | 0.6 |
| | 0.02 | 0.03 | 0.05 | 0.1 | 0.13 | 0.26 | 0.25 | 0.31 | 0.39 | 0.38 | 0.36 | 0.5 |
| | 0.02 | 0.02 | 0.03 | 0.06 | 0.1 | 0.13 | 0.18 | 0.25 | 0.29 | 0.33 | 0.35 | 0.4 |
| | 0.01 | 0.02 | 0.03 | 0.03 | 0.06 | 0.07 | 0.11 | 0.14 | 0.19 | 0.2 | 0.18 | 0.3 |
| | 0.01 | 0.01 | 0.02 | 0.03 | 0.04 | 0.04 | 0.05 | 0.06 | 0.07 | 0.08 | 0.07 | 0.2 |
| | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.1 |
| | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 |

### (Cultural Brokerage) − (Random)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 0.01 | 0.02 | 0.01 | 0.02 | 0.04 | 0.06 | 0.12 | 0.24 | 0.23 | 0 | 1 |
| | 0 | 0 | 0.04 | 0.04 | 0.01 | 0.02 | 0.07 | 0.15 | 0.14 | 0.25 | 0.33 | 0.9 |
| | 0 | -0.01 | -0.02 | 0.02 | 0.05 | 0.07 | 0.07 | 0.11 | 0.09 | 0.13 | 0.19 | 0.8 |
| | -0.01 | 0 | 0 | 0.04 | 0.02 | 0.05 | 0.04 | 0.05 | 0.09 | 0.16 | 0.14 | 0.7 |
| | 0.01 | 0 | 0 | 0 | 0.04 | 0.05 | 0.06 | 0.02 | 0.1 | 0.09 | 0.1 | 0.6 |
| | 0 | 0 | 0 | 0.01 | 0 | 0.02 | 0.02 | 0.05 | 0.05 | 0.06 | 0.06 | 0.5 |
| | 0.01 | 0 | 0 | 0 | 0 | 0.01 | -0.03 | 0.03 | 0.02 | 0.05 | 0.05 | 0.4 |
| | 0 | 0 | 0 | 0 | -0.01 | -0.03 | 0.02 | 0.02 | 0.02 | 0.04 | 0.02 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | -0.01 | 0.01 | 0 | -0.01 | 0.01 | -0.01 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | -0.01 | 0 | 0 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Cultural Brokerage) − (Popularity)

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 0 | 0.01 | -0.03 | 0.02 | 0.02 | 0.02 | 0.01 | 0.03 | 0 | 0 | 1 |
| | -0.01 | 0.02 | 0.04 | 0.02 | 0.02 | -0.01 | 0.02 | 0.06 | 0.03 | 0.03 | 0.04 | 0.9 |
| | 0 | 0.01 | 0.02 | 0 | 0.02 | 0.05 | 0.07 | 0.06 | 0.1 | 0.04 | 0.08 | 0.8 |
| | -0.01 | 0.01 | 0.01 | 0.03 | 0.04 | 0 | 0.01 | 0.02 | 0.09 | 0.11 | 0.08 | 0.7 |
| | 0 | 0 | -0.01 | -0.01 | 0.02 | 0.02 | 0.04 | 0.03 | 0.06 | 0.07 | 0.1 | 0.6 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.03 | 0.04 | 0.06 | 0.05 | 0.09 | 0.5 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.01 | -0.03 | 0.02 | 0.02 | 0.04 | 0.05 | 0.4 |
| | 0 | 0.01 | 0 | 0 | 0.01 | -0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | 0 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | -0.01 | 0 | -0.01 | -0.01 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### (Cultural Brokerage) − (Structural Brokerage)

**Baseline Model:**
N=300; Z=5; G=5; Q=10000; M=0; $T_{mean}$=0.5; $T_{mean}$=0.05

**Adoption**

0    0.4

152

**Baseline Model with Number of Secondary Boundaries (B) = 14**

## H O M O P H I L Y



**CONSOLIDATION** (vertical axis)

**(Cultural Brokerage) − (Random)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.01 | 0.02 | 0.08 | 0.27 | 0.37 | 0.44 | 0.41 | 0.45 | 0.43 | 0 |
| 0.9 | 0 | 0.01 | 0.02 | 0.08 | 0.24 | 0.33 | 0.34 | 0.47 | 0.49 | 0.47 | 0.49 |
| 0.8 | 0 | 0 | 0.01 | 0.06 | 0.17 | 0.37 | 0.39 | 0.42 | 0.44 | 0.47 | 0.46 |
| 0.7 | 0 | 0 | 0.01 | 0.05 | 0.18 | 0.3 | 0.36 | 0.39 | 0.41 | 0.46 | 0.51 |
| 0.6 | 0 | 0 | 0.01 | 0.04 | 0.12 | 0.25 | 0.31 | 0.35 | 0.38 | 0.41 | 0.43 |
| 0.5 | 0 | 0 | 0.01 | 0.02 | 0.09 | 0.17 | 0.29 | 0.29 | 0.37 | 0.34 | 0.38 |
| 0.4 | 0 | 0 | 0.01 | 0.03 | 0.06 | 0.13 | 0.23 | 0.28 | 0.29 | 0.32 | 0.34 |
| 0.3 | 0 | 0 | 0.01 | 0.01 | 0.03 | 0.07 | 0.11 | 0.16 | 0.2 | 0.17 | 0.16 |
| 0.2 | 0 | 0 | 0.01 | 0.01 | 0.03 | 0.05 | 0.06 | 0.08 | 0.08 | 0.08 | 0.07 |
| 0.1 | 0 | 0 | 0 | 0.01 | 0.02 | 0.03 | 0.03 | 0.04 | 0.02 | 0.02 | 0.02 |
| 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 |

**(Cultural Brokerage) − (Popularity)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.03 | 0.07 | 0.08 | 0.14 | 0.19 | 0.27 | 0.31 | 0 |
| 0.9 | 0 | 0 | 0 | 0.01 | 0 | 0.05 | 0.07 | 0.16 | 0.2 | 0.23 | 0.29 |
| 0.8 | 0 | 0 | 0 | 0.01 | 0.05 | 0.06 | 0.11 | 0.11 | 0.14 | 0.16 | 0.26 |
| 0.7 | 0 | 0 | 0 | 0 | 0.02 | 0.01 | 0.04 | 0.08 | 0.07 | 0.14 | 0.12 |
| 0.6 | 0 | 0 | 0 | 0.01 | 0 | 0.03 | 0.05 | 0.05 | 0.03 | 0.09 | 0.08 |
| 0.5 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0.02 | 0.03 | 0.04 | 0.05 | 0.04 |
| 0.4 | 0 | 0 | 0 | 0.01 | 0 | 0.01 | 0.07 | 0.07 | 0.05 | 0.02 | 0.04 |
| 0.3 | 0 | 0 | 0 | 0 | -0.01 | 0.01 | 0.01 | 0.04 | 0.02 | 0.01 | -0.01 |
| 0.2 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | 0.01 | 0.01 | 0 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | -0.01 | -0.01 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) − (Structural Brokerage)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.02 | 0.07 | 0.07 | 0.05 | 0.07 | 0.1 | 0.01 | 0 |
| 0.9 | 0 | 0 | 0 | 0.03 | 0.01 | 0.08 | 0.04 | 0.1 | 0.07 | 0.1 | 0.03 |
| 0.8 | 0 | 0 | 0 | 0.02 | 0.03 | 0.04 | 0.06 | 0.05 | 0.07 | 0.09 | 0.07 |
| 0.7 | 0 | 0 | 0 | 0 | 0.03 | 0.03 | 0.04 | 0.07 | 0.02 | 0.1 | 0.08 |
| 0.6 | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.05 | 0.05 | 0.03 | 0.06 | 0.07 |
| 0.5 | 0 | 0 | 0 | -0.01 | 0.01 | -0.01 | 0.03 | 0.05 | 0.06 | 0.01 | 0.05 |
| 0.4 | 0 | 0 | 0 | 0.01 | -0.01 | 0 | 0.07 | 0.03 | 0.06 | 0.05 | 0.03 |
| 0.3 | 0 | 0 | 0 | 0 | -0.02 | -0.01 | 0 | 0.02 | 0.02 | 0.02 | 0.02 |
| 0.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0.02 | 0.01 | -0.01 |
| 0.1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0 | 0 | 0 |

**Baseline Model:**
$N=300$; $Z=5$; $G=5$; $Q=10000$; $M=0$; $T_{mean}=0.5$; $T_{mean}=0.05$

**Adoption**

0    0.4

# Baseline Model with Number of Iterations (Q) = 50000

## HOMOPHILY

**CONSOLIDATION**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 0.02 | 0.04 | 0.12 | 0.25 | 0.33 | 0.35 | 0.42 | 0.41 | 0.39 | 0 | 1 |
| | 0.01 | 0.01 | 0.05 | 0.12 | 0.24 | 0.3 | 0.39 | 0.45 | 0.46 | 0.43 | 0.44 | 0.9 |
| | 0.01 | 0.01 | 0.03 | 0.08 | 0.23 | 0.3 | 0.43 | 0.43 | 0.49 | 0.47 | 0.46 | 0.8 |
| | 0.01 | 0.01 | 0.03 | 0.09 | 0.2 | 0.26 | 0.32 | 0.41 | 0.42 | 0.39 | 0.48 | 0.7 |
| | 0.01 | 0.01 | 0.03 | 0.07 | 0.13 | 0.22 | 0.33 | 0.33 | 0.38 | 0.41 | 0.41 | 0.6 |
| | 0 | 0.01 | 0.02 | 0.05 | 0.09 | 0.14 | 0.24 | 0.32 | 0.35 | 0.37 | 0.37 | 0.5 |
| | 0 | 0.01 | 0.01 | 0.03 | 0.09 | 0.12 | 0.17 | 0.23 | 0.25 | 0.27 | 0.27 | 0.4 |
| | 0 | 0 | 0.01 | 0.03 | 0.04 | 0.08 | 0.12 | 0.16 | 0.18 | 0.17 | 0.22 | 0.3 |
| | 0 | 0 | 0.01 | 0.02 | 0.03 | 0.05 | 0.06 | 0.07 | 0.08 | 0.09 | 0.1 | 0.2 |
| | 0 | 0 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.1 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 |

**(Cultural Brokerage) – (Random)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | -0.01 | 0.07 | 0.06 | 0.08 | 0.15 | 0.21 | 0.26 | 0.25 | 0 | 1 |
| | 0 | 0 | 0.02 | -0.01 | 0.03 | 0.06 | 0.12 | 0.12 | 0.19 | 0.19 | 0.26 | 0.9 |
| | 0 | 0 | 0 | -0.01 | 0.07 | 0.08 | 0.12 | 0.14 | 0.18 | 0.19 | 0.24 | 0.8 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.03 | 0.09 | 0.08 | 0.12 | 0.19 | 0.7 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.03 | 0.04 | 0.06 | 0.12 | 0.06 | | 0.6 |
| | 0 | 0 | 0 | 0 | -0.02 | 0 | 0.03 | 0.03 | 0.04 | 0.09 | 0.08 | 0.5 |
| | 0 | 0 | 0 | 0 | 0.03 | 0 | 0.01 | 0 | 0.04 | 0.02 | 0.04 | 0.4 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.04 | 0.02 | 0.02 | 0.02 | 0.3 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0 | -0.01 | 0 | 0.01 | | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) – (Popularity)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | 0 | 0.06 | 0.04 | 0.07 | 0.09 | 0.07 | -0.04 | 0 | 1 |
| | 0 | 0 | 0.01 | 0.03 | 0.04 | 0.02 | 0.1 | 0.05 | 0.08 | -0.03 | 0.02 | 0.9 |
| | 0 | 0 | 0 | 0 | 0.05 | 0.03 | 0.05 | 0.11 | 0.09 | 0.12 | 0.08 | 0.8 |
| | 0 | 0 | 0 | 0.01 | 0.02 | 0.02 | 0.04 | 0.08 | 0.08 | 0.08 | 0.11 | 0.7 |
| | 0 | 0 | 0.01 | 0.02 | -0.01 | -0.01 | 0.04 | 0.03 | 0.06 | 0.07 | 0.07 | 0.6 |
| | 0 | 0 | 0.01 | 0.01 | 0.03 | 0.01 | 0.03 | 0.05 | 0.04 | 0.09 | 0.09 | 0.5 |
| | 0 | 0 | 0 | 0 | 0.02 | 0 | 0.01 | 0 | 0 | 0.05 | 0.01 | 0.4 |
| | 0 | 0 | 0 | 0.01 | 0 | 0 | 0.02 | 0.02 | 0.01 | 0 | 0.02 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | -0.01 | -0.02 | 0 | -0.02 | 0.01 | 0.01 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) – (Structural Brokerage)**

**Baseline Model:**
N=300; Z=5; G=5; B=9; M=0; $T_{mean}$=0.5; $T_{mean}$=0.05

**Adoption**

0        0.4

# Baseline Model with Behavioral Noise (Q) = 0.01

## H  O  M  O  P  H  I  L  Y

**C O N S O L I D A T I O N**

| 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.01 | 0.03 | 0.14 | 0.24 | 0.31 | 0.39 | 0.4 | 0.4 | 0.39 | 0 | 1 |
| 0.01 | 0.01 | 0.03 | 0.13 | 0.25 | 0.36 | 0.39 | 0.46 | 0.42 | 0.46 | 0.46 | 0.9 |
| 0.01 | 0.01 | 0.03 | 0.08 | 0.21 | 0.27 | 0.37 | 0.39 | 0.43 | 0.48 | 0.48 | 0.8 |
| 0.01 | 0.01 | 0.01 | 0.06 | 0.19 | 0.29 | 0.33 | 0.37 | 0.4 | 0.45 | 0.47 | 0.7 |
| 0.01 | 0.01 | 0.02 | 0.04 | 0.15 | 0.24 | 0.29 | 0.41 | 0.34 | 0.44 | 0.42 | 0.6 |
| 0 | 0.01 | 0.02 | 0.03 | 0.1 | 0.16 | 0.26 | 0.33 | 0.37 | 0.33 | 0.39 | 0.5 |
| 0 | 0.01 | 0.01 | 0.02 | 0.05 | 0.13 | 0.18 | 0.26 | 0.3 | 0.27 | 0.33 | 0.4 |
| 0 | 0 | 0.01 | 0.01 | 0.05 | 0.08 | 0.1 | 0.12 | 0.16 | 0.17 | 0.19 | 0.3 |
| 0 | 0 | 0.01 | 0.01 | 0.02 | 0.03 | 0.05 | 0.08 | 0.05 | 0.07 | 0.06 | 0.2 |
| 0 | 0 | 0 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.02 | 0.02 | 0.1 |
| 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 | 0 |

0  0.1  0.2  0.3  0.4  0.5  0.6  0.7  0.8  0.9  1

**(Cultural Brokerage) – (Random)**

| 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.01 | 0 | 0.04 | 0.07 | 0.08 | 0.13 | 0.24 | 0.23 | 0.29 | 0 | 1 |
| 0 | 0 | 0 | 0.04 | 0.05 | 0.09 | 0.1 | 0.16 | 0.16 | 0.25 | 0.29 | 0.9 |
| 0 | 0 | 0 | 0.01 | 0.03 | 0.02 | 0.1 | 0.16 | 0.17 | 0.21 | 0.18 | 0.8 |
| 0 | 0 | 0 | 0 | 0.05 | 0.08 | 0.06 | 0.06 | 0.08 | 0.19 | 0.16 | 0.7 |
| 0 | 0 | 0 | 0 | 0.03 | 0.07 | 0.08 | 0.09 | 0.04 | 0.1 | 0.11 | 0.6 |
| 0 | 0 | 0 | 0 | 0.01 | -0.01 | 0.04 | 0.02 | 0.03 | 0.07 | 0.08 | 0.5 |
| 0 | 0 | 0 | 0 | -0.01 | 0.03 | 0.04 | 0.03 | 0.03 | 0.04 | 0.04 | 0.4 |
| 0 | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0 | 0.03 | 0 | 0.04 | 0.3 |
| 0 | 0 | 0 | 0 | 0 | -0.01 | 0 | 0 | -0.01 | 0.01 | -0.01 | 0.2 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

0  0.1  0.2  0.3  0.4  0.5  0.6  0.7  0.8  0.9  1

**(Cultural Brokerage) – (Popularity)**

| 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0.03 | 0.03 | 0.08 | 0.04 | 0.1 | 0.03 | 0.01 | 0 | 1 |
| 0 | 0 | 0 | 0.03 | 0.03 | 0.08 | 0.03 | 0.06 | 0.06 | 0.07 | 0.06 | 0.9 |
| 0 | 0 | 0 | 0 | 0.03 | 0.02 | 0.08 | 0.1 | 0.12 | 0.11 | 0.09 | 0.8 |
| 0 | 0 | -0.01 | 0 | 0.04 | 0.06 | 0.07 | 0.05 | 0.06 | 0.12 | 0.12 | 0.7 |
| 0 | 0 | 0 | 0 | 0 | 0.03 | 0.06 | 0.06 | 0.05 | 0.12 | 0.1 | 0.6 |
| 0 | 0 | 0 | 0 | 0 | 0.02 | 0.04 | 0.02 | 0.04 | 0.04 | 0.05 | 0.5 |
| 0 | 0 | 0 | 0 | -0.02 | 0.04 | 0.02 | 0.04 | 0.05 | 0.02 | 0.06 | 0.4 |
| 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0 | 0 | 0.01 | 0.01 | 0 | 0.3 |
| 0 | 0 | 0 | 0 | 0 | -0.01 | -0.01 | 0.01 | 0 | 0.01 | 0 | 0.2 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.1 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

0  0.1  0.2  0.3  0.4  0.5  0.6  0.7  0.8  0.9  1

**(Cultural Brokerage) – (Structural Brokerage)**

**Baseline Model:**

N=300; Z=5; G=5; B=9; M = 10000; $T_{mean}$=0.5; $T_{mean}$=0.05

**Adoption**

0    0.4

155

# Baseline Model with Behavioral Noise (Q) = 0.025

## H O M O P H I L Y



(Cultural Brokerage) − (Random)

(Cultural Brokerage) − (Popularity)

(Cultural Brokerage) − (Structural Brokerage)

**Baseline Model:**
N=300; Z=5; G=5; B=9; M = 10000; $T_{mean}$=0.5; $T_{mean}$=0.05

**Adoption**

0    0.4

# Baseline Model with Behavioral Noise (Q) = 0.05

## H O M O P H I L Y

**CONSOLIDATION**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0.01 | 0.02 | 0.09 | 0.23 | 0.36 | 0.37 | 0.45 | 0.4 | 0.39 | 0 | 1 |
| | 0 | 0.01 | 0.02 | 0.08 | 0.23 | 0.34 | 0.35 | 0.43 | 0.4 | 0.47 | 0.44 | 0.9 |
| | 0 | 0.01 | 0.01 | 0.06 | 0.17 | 0.33 | 0.36 | 0.35 | 0.44 | 0.45 | 0.43 | 0.8 |
| | 0 | 0.01 | 0.02 | 0.05 | 0.11 | 0.23 | 0.33 | 0.38 | 0.41 | 0.45 | 0.49 | 0.7 |
| | 0 | 0 | 0.01 | 0.03 | 0.08 | 0.2 | 0.26 | 0.34 | 0.43 | 0.39 | 0.44 | 0.6 |
| | 0 | 0 | 0.01 | 0.03 | 0.06 | 0.13 | 0.23 | 0.32 | 0.34 | 0.36 | 0.39 | 0.5 |
| | 0 | 0 | 0.01 | 0.02 | 0.04 | 0.07 | 0.13 | 0.2 | 0.23 | 0.24 | 0.31 | 0.4 |
| | 0 | 0 | 0.01 | 0.01 | 0.03 | 0.04 | 0.05 | 0.09 | 0.1 | 0.11 | 0.16 | 0.3 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.2 |
| | 0 | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) − (Random)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0.01 | 0.01 | 0.03 | 0.11 | 0.08 | 0.23 | 0.19 | 0.24 | 0 | 1 |
| | 0 | 0 | 0 | 0.01 | 0.02 | 0.1 | 0.1 | 0.14 | 0.17 | 0.22 | 0.26 | 0.9 |
| | 0 | 0 | 0 | 0.01 | 0.04 | 0.04 | 0.08 | 0.11 | 0.19 | 0.19 | 0.19 | 0.8 |
| | 0 | 0 | 0.01 | 0.01 | 0.01 | 0.03 | 0.04 | 0.06 | 0.11 | 0.11 | 0.17 | 0.7 |
| | 0 | 0 | 0 | -0.01 | 0.01 | 0.03 | 0.03 | 0.13 | 0.05 | 0.07 | 0.16 | 0.6 |
| | 0 | 0 | 0 | 0 | -0.01 | 0.01 | 0.03 | 0.08 | 0.07 | 0.05 | 0.05 | 0.5 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.01 | 0.02 | 0.04 | 0 | 0.01 | 0.04 | 0.4 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.02 | 0.03 | 0.02 | 0.01 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | -0.01 | 0 | 0.01 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) − (Popularity)**

| | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 0 | 0 | -0.01 | 0.05 | 0.05 | 0.02 | 0.1 | 0.04 | 0.03 | 0 | 1 |
| | 0 | 0 | 0 | 0.02 | 0.03 | 0.08 | 0.07 | 0.09 | 0.04 | 0.06 | 0.05 | 0.9 |
| | 0 | 0 | 0 | 0.02 | 0.02 | 0.11 | 0.05 | 0.06 | 0.1 | 0.08 | 0.08 | 0.8 |
| | 0 | 0 | 0.01 | 0 | 0 | 0.03 | 0.04 | 0.07 | 0.04 | 0.1 | 0.08 | 0.7 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.02 | 0 | 0.05 | 0.07 | 0.04 | 0.13 | 0.6 |
| | 0 | 0 | 0 | 0 | 0.01 | 0.02 | 0.05 | 0.05 | 0.06 | 0.08 | 0.09 | 0.5 |
| | 0 | 0 | 0 | 0.01 | 0 | 0 | 0.03 | 0.05 | -0.01 | 0.04 | 0.04 | 0.4 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.02 | 0.01 | 0.02 | 0.3 |
| | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0 | -0.01 | -0.01 | 0 | 0.2 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0 | 0.1 |
| | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**(Cultural Brokerage) − (Structural Brokerage)**

**Baseline Model:**

$N=300$; $Z=5$; $G=5$; $B=9$; $M = 10000$; $T_{mean}=0.5$; $T_{mean}=0.05$

**Adoption**

0    0.4

157

**Baseline Model with Behavioral Noise (Q) = 0.1**

**H O M O P H I L Y**

**CONSOLIDATION**

(Cultural Brokerage) − (Random)

(Cultural Brokerage) − (Popularity)

(Cultural Brokerage) − (Structural Brokerage)

**Baseline Model:**
N=300; Z=5; G=5; B=9; $T_{mean}$=0.5; $T_{mean}$=0.05

**Adoption**

0   0.4

## APPENDIX A.2.1
## Descriptive Statistics Jefferson High

| Variable Name | Mean or Percent | SD | Range |
|---|---|---|---|
| Age | 15.03 | 1.10 | 12 – 19 |
| Income | 49.38 | 25.94 | 3 – 200 |
| BMI | 22.91 | 4.37 | 13.8 – 44.3 |
| Grade | 10.04 | 0.97 | 7 – 12 |
| Men | 47.19% | | 0 – 1 |
| Latino | 0.81% | | 0 – 1 |
| White | 94.69% | | 0 – 1 |
| Black | 0% | | 0 – 1 |
| Asian | 0.32% | | 0 – 1 |
| Native | 0.32% | | 0 – 1 |
| Multiracial | 4.51% | | 0 – 1 |
| Average # in-ties | 3.10 | 0.07 | 0 – 17 |

## APPENDIX A.2.2
## Replication of SAOM Estimates Reported by Shoham et al. 2012 and Zhang et al. 2015a Testing Friendship Nominations and BMI Coevolution in Jefferson High

| Friendship Nomination (Network) Function | b | S.E. |
|---|---|---|
| Basic rate parameter network change | 12.75 | |
| Out-degree (density) | -3.56*** | (0.04) |
| Reciprocity | 2.25*** | (0.07) |
| Number of transitive triplets | 0.49*** | (0.03) |
| Same sex | 0.19*** | (0.04) |
| Same grade | 0.46*** | (0.04) |
| Similarity on age | 1.22*** | (0.19) |
| Similarity on income | 0.08 | (0.15) |
| BMI ego | -0.05** | (0.02) |
| BMI alter | 0.03 | (0.02) |
| Similarity on BMI | 0.41* | (0.22) |
| **BMI (Behavior) Function** | | |
| Basic rate parameter behavior change | 0.95 | |
| BMI linear shape | 1.39* | (0.72) |
| BMI quadratic shape | 0.28 | (0.24) |
| BMI average similarity | 22.14 | (14.88) |

*p. < 0.1; **p. <0.05; ** p. <0.001

## APPENDIX A.3.1
### List of Countries Included in the Estimation of Migration Flows (N = 192)

| Country Name | Region |
|---|---|
| Afghanistan | South Asia |
| Albania | Eastern Europe and Central Asia |
| Algeria | Rest of Middle East and North Africa |
| Angola | Africa |
| Antigua and Barbuda | Latin America and the Caribbean |
| Argentina | Latin America and the Caribbean |
| Armenia | Eastern Europe and Central Asia |
| Aruba | Latin America and the Caribbean |
| Australia | Australia and New Zealand |
| Austria | Western Europe |
| Azerbaijan | Eastern Europe and Central Asia |
| Bahamas, The | Latin America and the Caribbean |
| Bahrain | High Income Middle East and N. Africa |
| Bangladesh | South Asia |
| Barbados | Latin America and the Caribbean |
| Belarus | Eastern Europe and Central Asia |
| Belgium | Western Europe |
| Belize | Latin America and the Caribbean |
| Benin | Africa |
| Bhutan | South Asia |
| Bolivia | Latin America and the Caribbean |
| Bosnia and Herzegovina | Eastern Europe and Central Asia |
| Botswana | Africa |
| Brazil | Latin America and the Caribbean |
| Brunei Darussalam | East Asia and the Pacific |
| Bulgaria | Eastern Europe and Central Asia |
| Burkina Faso | Africa |
| Burundi | Africa |
| Cambodia | East Asia and the Pacific |
| Cameroon | Africa |
| Canada | Canada |
| Cape Verde | Africa |
| Central African Republic | Africa |
| Chad | Africa |
| Chile | Latin America and the Caribbean |
| China | East Asia and the Pacific |
| Colombia | Latin America and the Caribbean |
| Comoros | Africa |
| Congo, Dem. Rep. | Africa |
| Congo, Rep. | Africa |
| Costa Rica | Latin America and the Caribbean |
| Cote d'Ivoire | Africa |
| Croatia | Eastern Europe and Central Asia |

| | |
|---|---|
| Cuba | Latin America and the Caribbean |
| Cyprus | Western Europe |
| Czech Republic | Eastern Europe and Central Asia |
| Denmark | Western Europe |
| Djibouti | Africa |
| Dominican Republic | Latin America and the Caribbean |
| Ecuador | Latin America and the Caribbean |
| Egypt, Arab Rep. | Rest of Middle East and North Africa |
| El Salvador | Latin America and the Caribbean |
| Equatorial Guinea | Africa |
| Eritrea | Africa |
| Estonia | Eastern Europe and Central Asia |
| Ethiopia | Africa |
| Fiji | East Asia and the Pacific |
| Finland | Western Europe |
| France | Western Europe |
| French Guiana | Latin America and the Caribbean |
| French Polynesia | East Asia and the Pacific |
| Gabon | Africa |
| Gambia, The | Africa |
| Georgia | Eastern Europe and Central Asia |
| Germany | Western Europe |
| Ghana | Africa |
| Greece | Western Europe |
| Grenada | Latin America and the Caribbean |
| Guadeloupe | Latin America and the Caribbean |
| Guatemala | Latin America and the Caribbean |
| Guinea | Africa |
| Guinea-Bissau | Africa |
| Guyana | Latin America and the Caribbean |
| Haiti | Latin America and the Caribbean |
| Honduras | Latin America and the Caribbean |
| Hong Kong SAR, China | East Asia and the Pacific |
| Hungary | Eastern Europe and Central Asia |
| Iceland | Western Europe |
| India | South Asia |
| Indonesia | East Asia and the Pacific |
| Iran, Islamic Rep. | Rest of Middle East and North Africa |
| Iraq | Rest of Middle East and North Africa |
| Ireland | Western Europe |
| Israel | High Income Middle East and N. Africa |
| Italy | Western Europe |
| Jamaica | Latin America and the Caribbean |
| Japan | Japan |
| Jordan | Rest of Middle East and North Africa |
| Kazakhstan | Eastern Europe and Central Asia |
| Kenya | Africa |
| Kiribati | East Asia and the Pacific |

| | |
|---|---|
| Korea, Dem. Rep. | East Asia and the Pacific |
| Korea, Rep. | East Asia and the Pacific |
| Kuwait | High Income Middle East and N. Africa |
| Kyrgyz Republic | Eastern Europe and Central Asia |
| Lao PDR | East Asia and the Pacific |
| Latvia | Eastern Europe and Central Asia |
| Lebanon | Rest of Middle East and North Africa |
| Lesotho | Africa |
| Liberia | Africa |
| Libya | Rest of Middle East and North Africa |
| Lithuania | Eastern Europe and Central Asia |
| Luxembourg | Western Europe |
| Macao SAR, China | East Asia and the Pacific |
| Macedonia, FYR | Eastern Europe and Central Asia |
| Madagascar | Africa |
| Malawi | Africa |
| Malaysia | East Asia and the Pacific |
| Maldives | South Asia |
| Mali | Africa |
| Malta | Western Europe |
| Martinique | Latin America and the Caribbean |
| Mauritania | Africa |
| Mauritius | Africa |
| Mexico | Latin America and the Caribbean |
| Micronesia, Fed. Sts. | East Asia and the Pacific |
| Moldova | Eastern Europe and Central Asia |
| Mongolia | East Asia and the Pacific |
| Morocco | Rest of Middle East and N. Africa |
| Mozambique | Africa |
| Myanmar | East Asia and the Pacific |
| Namibia | Africa |
| Nepal | South Asia |
| Netherlands | Western Europe |
| New Caledonia | East Asia and the Pacific |
| New Zealand | Australia and New Zealand |
| Nicaragua | Latin America and the Caribbean |
| Niger | Africa |
| Nigeria | Africa |
| Norway | Western Europe |
| Oman | High Income Middle East and N. Africa |
| Pakistan | South Asia |
| Panama | Latin America and the Caribbean |
| Papua New Guinea | East Asia and the Pacific |
| Paraguay | Latin America and the Caribbean |
| Peru | Latin America and the Caribbean |
| Philippines | East Asia and the Pacific |
| Poland | Eastern Europe and Central Asia |
| Portugal | Western Europe |

| | |
|---|---|
| Puerto Rico | Latin America and the Caribbean |
| Qatar | High Income Middle East and N. Africa |
| Reunion | Africa |
| Romania | Eastern Europe and Central Asia |
| Russian Federation | Eastern Europe and Central Asia |
| Rwanda | Africa |
| Samoa | East Asia and the Pacific |
| Sao Tome and Principe | Africa |
| Saudi Arabia | High Income Middle East and N. Africa |
| Senegal | Africa |
| Serbia and Montenegro | Eastern Europe and Central Asia |
| Sierra Leone | Africa |
| Singapore | East Asia and the Pacific |
| Slovak Republic | Eastern Europe and Central Asia |
| Slovenia | Eastern Europe and Central Asia |
| Solomon Islands | East Asia and the Pacific |
| Somalia | Africa |
| South Africa | Africa |
| Spain | Western Europe |
| Sri Lanka | South Asia |
| St. Lucia | Latin America and the Caribbean |
| St. Vincent and the Grenadines | Latin America and the Caribbean |
| Sudan | Africa |
| Suriname | Latin America and the Caribbean |
| Swaziland | Africa |
| Sweden | Western Europe |
| Switzerland | Western Europe |
| Syrian Arab Republic | Rest of Middle East and North Africa |
| Taiwan, China | East Asia and the Pacific |
| Tajikistan | Eastern Europe and Central Asia |
| Tanzania | Africa |
| Thailand | East Asia and the Pacific |
| Timor-Leste | East Asia and the Pacific |
| Togo | Africa |
| Tonga | East Asia and the Pacific |
| Trinidad and Tobago | Latin America and the Caribbean |
| Tunisia | Rest of Middle East and North Africa |
| Turkey | Eastern Europe and Central Asia |
| Turkmenistan | Eastern Europe and Central Asia |
| Uganda | Africa |
| Ukraine | Eastern Europe and Central Asia |
| United Arab Emirates | High Income Middle East and N. Africa |
| United Kingdom | Western Europe |
| United States | United States |
| Uruguay | Latin America and the Caribbean |
| Uzbekistan | Eastern Europe and Central Asia |
| Vanuatu | East Asia and the Pacific |
| Venezuela, RB | Latin America and the Caribbean |

| | |
|---|---|
| Vietnam | East Asia and the Pacific |
| West Bank and Gaza | Rest of Middle East and North Africa |
| Yemen, Rep. | Rest of Middle East and North Africa |
| Zambia | Africa |
| Zimbabwe | Africa |

- Original bilateral migrant stock data produced by the World Bank can be downloaded from https://bit.ly/2tXTcI9
- Original data on total population per country produced by the UN Population Division can be downloaded from https://bit.ly/2cnUFD4
- Original data on number of deaths per country produced by the UN Population Division can be downloaded from https://bit.ly/2tNtkj7
- Original data on number of births per country produced by the UN Population Division can be downloaded from https://bit.ly/2tZp7I9
- Taiwan's total population, number of births, and number of deaths data can be downloaded from https://bit.ly/2KDX0bP
- Original *Adjusted Income per Capita Index* is developed by Padros de la Escosura (2015). The raw data can be downloaded from https://bit.ly/2KuEJyo .Since the original data ranges from 0 to 1 with a three-decimal point format, each original value was multiplied by 100.
- Original *Major Episodes of Political Violence (MEPV) 1946-2015 data set* developed by the Center for Systematic Piece codebook and data can be accessed https://bit.ly/1RD6fl7 This data set lists annual time-series data on political violence. I manually added Bahamas, Barbados, Belize, Jamaica, Puerto Rico, St Vincent and the Grenadines, and St. Lucia which were not in the original data set but did not have any major political conflicts between 1946-2015. I also completed the entries for Jamaica (1946 to 1961 were absent), Guyana (1946 to 1965 were absent), Suriname (1946 to 1974 were absent) and Trinidad (1946 to 1961 were absent). None of these four countries had major episodes of political violence during those years. Importantly, the MEPV does not include in the count of major episodes of political violence any conflict related to independence (see codebook).
- Geographic distance between countries in the world can be downloaded from https://bit.ly/2KEXfAd
  - The original data file can be downloaded after clicking on the hyperlink "dist_cepii.dta" on page 2. The original file is a STATA data file (dist_cepii.dta). Therefore, the data set was opened in STATA 13 and save as a .csv file.

The UN data (i.e. population, births, deaths) originally are in thousands, so before saving these three data sheets in .csv format, all cell containing data were multiplied by 1000. This is important because if the data sheets are directly saved in .csv format, the decimal points are lost.

**Code**
All the relevant code to estimate migration flows and fit TERG models, as well as the raw input data files used in Chapter 3, can be downloaded as R objects from www.diegoleal.info

**APPENDIX A.3.3**
**Countries in the Americas Included in the Analysis (N = 38)**

| Country | Subregion |
| --- | --- |
| Antigua and Barbuda | Caribbean |
| Argentina | Southern Cone |
| Aruba | Caribbean |
| Bahamas, The | Caribbean |
| Barbados | Caribbean |
| Belize | Central America |
| Bolivia | Andes |
| Brazil | Southern Cone |
| Canada | North America |
| Chile | Southern Cone |
| Colombia | Andes |
| Costa Rica | Central America |
| Cuba | Caribbean |
| Dominican Republic | Caribbean |
| Ecuador | Andes |
| El Salvador | Central America |
| French Guiana | Caribbean |
| Grenada | Caribbean |
| Guadeloupe | Caribbean |
| Guatemala | Central America |
| Guyana | Caribbean |
| Haiti | Caribbean |
| Honduras | Central America |
| Jamaica | Caribbean |
| Martinique | Caribbean |
| Mexico | North America |
| Nicaragua | Central America |
| Panama | Central America |
| Paraguay | Southern Cone |
| Peru | Andes |
| Puerto Rico | Caribbean |
| St Lucia | Caribbean |
| St Vincent and the Grenadines | Caribbean |
| Suriname | Caribbean |
| Trinidad and Tobago | Caribbean |
| United States | North America |
| Uruguay | Southern Cone |
| Venezuela, RB | Andes |

| LABELS | | | | |
|---|---|---|---|---|
| | **Parallel** | **Font** | **Size** | **Color** |
| **Segment** | Yes | Normal | Med | Black |
| **Tick** | No | Light | Small | Black |
| **Segment labels inside segments** | Unchecked | | | |

| DATA FILTERS | | | | |
|---|---|---|---|---|
| **Cell percentile cutoff** | 0 | | **Intra-segment cells** | Show |

| VALUE REMAPPING | |
|---|---|
| **Attenuate small values** | Unchecked |

| ROW AND COLUMN SEGMENTS | | | | | | |
|---|---|---|---|---|---|---|
| **Thickness** | thin | **Spacing** | very loose | **radius** | Large |
| **Order** | name | **Progression** | Desc | **Normalize segment size** | No |

| CELL RIBBONS | | | | | |
|---|---|---|---|---|---|
| **Ribbon placement on segments** | Row ribbon first | **Ribbon order** | Destination segment position | **Ribbon layer order** | Large on top of small |
| **Reverse row and column ribbon position** | Unchecked | **Default Transparency** | 2 | | |

| QUARTILE RIBBONS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Q1** | Unchecked | **Color** | (blank) | **Transparency** | (blank) | **Stroke** | Yes |
| **Q2** | Unchecked | **Color** | (blank) | **Transparency** | (blank) | **Stroke** | Yes |
| **Q3** | Unchecked | **Color** | (blank) | **Transparency** | (blank) | **Stroke** | Yes |
| **Q4** | Unchecked | **Color** | (blank) | **Transparency** | (blank) | **Stroke** | Yes |

| CONTRIBUTION TRACKS | | | | | |
|---|---|---|---|---|---|
| **Hide** | checked | **Expand size to segment size** | Unchecked | **No stroke** | Unchecked |

| RIBBON CAPS | | | | | |
|---|---|---|---|---|---|
| **hide ribbon caps colored by row** | Unchecked | **no stroke** | Unchecked | **hide ribbon caps colored by column** | Unchecked |

| RATIO LAYOUT | | | | | |
|---|---|---|---|---|---|
| **Use ratio layout** | Unchecked | | | | |
| **Start segments at 3 o'clock** | checked | **Hide first tick label** | checked | **No stroke on any segment** | Unchecked |
| **Draw last tick (seg. size)** | Unchecked | **Hide segment labels** | Unchecked | **Hide absolute tick marks** | checked |
| **Hide all tick labels** | Unchecked | **Hide relevant tick marks** | checked | | |

| COLORS | | | | | | |
|---|---|---|---|---|---|---|
| **Colors ribbon by** | row | **Colors ribbons by value** | no | **Segment color order** | Segment label | **Seg color interpolation** | By count |

**Input data files** can be obtained by running the relevant code (see Appendix A.3.1). Once data files are obtained, make sure you delete all the quotation marks "" around the column and row names of the flow matrices, and writing "DAT" in cell [1,1] of all flow matrices, the circos plots used in the paper can be reproduced using a web application (http://mkweb.bcgsc.ca/tableviewer/) with settings detailed in the table above.

**Sociograms of the Migration Flows in the Americas by Thresholding Rule**

Thresholding = top 10 destinations

Mean percent flows present out
of all flows observed = 40.08%

Mean Graph Density 0.298



Thresholding = top 15 destinations

Mean percent flows present out
of all flows  = 60.23%

Mean Graph Density 0.449



Thresholding = top 20 destinations

Mean percent flows present out
of all flows observed = 79.95%

Mean Graph Density = 0.595

**In-degree Distributions with Thresholding = 15, Migration Flows in the Americas, 1960 – 2000**

**TERGM to Investigate International Migration Flows in the Americas, 1960-2000.**
**Robustness checks**

**Thresholding = Top 10 Destination Countries**

| | Estimates | | Lower Bound CI | Upper Bound CI |
|---|---|---|---|---|
| Intercept/edges | 15.369 | *** | 11.627 | 26.253 |
| Endogenous dependencies | | | | |
| Transitive triads | 0.222 | *** | 0.153 | 0.316 |
| Cyclic triads | -0.245 | *** | -0.433 | -0.149 |
| Endogenous controls | | | | |
| In-degree popularity | 0.179 | *** | 0.062 | 0.334 |
| Out-degree popularity | -4.293 | *** | -6.631 | -3.721 |
| Mutuality | 0.635 | *** | 0.233 | 1.398 |
| Delayed reciprocity | 0.376 | *** | 0.156 | 0.931 |
| Dyadic stability | 0.612 | *** | 0.408 | 0.978 |
| Outdegree absolute diff | -4.343 | *** | -8.060 | -3.206 |
| Exogenous controls | | | | |
| Same region | 0.656 | *** | 0.807 | 1.044 |
| Same language | 0.605 | *** | 0.357 | 1.234 |
| Income * indegree | 0.001 | | -0.001 | 0.002 |
| Income * outdegree | 0.001 | *** | 0.001 | 0.002 |
| Conflict * indegree | 0.001 | | 0.005 | 0.014 |
| Conflict * outdegree | 0.007 | *** | 0.005 | 0.017 |

P-value thresholds (two sided): + < 0.1, * < 0.05, ** < 0.001

**Thresholding = Top 20 Destination Countries**

| | Estimates | | Lower Bound CI | Upper Bound CI |
|---|---|---|---|---|
| Intercept/edges | -1.965 | | -4.248 | 1.491 |
| **Endogenous dependencies** | | | | |
| Transitive triads | 0.082 | *** | 0.064 | 0.126 |
| Cyclic triads | -0.107 | *** | -0.140 | -0.073 |
| **Endogenous controls** | | | | |
| In-degree popularity | 0.301 | * | 0.190 | 0.411 |
| Out-degree popularity | -0.380 | *** | -1.606 | -0.041 |
| Mutuality | 0.559 | *** | 0.400 | 0.732 |
| Delayed reciprocity | 0.251 | *** | 0.156 | 0.503 |
| Dyadic stability | 0.414 | *** | 0.265 | 0.647 |
| Outdegree absolute diff | 0.359 | *** | -0.664 | -0.127 |
| **Exogenous controls** | | | | |
| Same region | 1.004 | *** | 0.649 | 1.134 |
| Same language | 0.593 | *** | 0.332 | 0.719 |
| Income * indegree | 0.001 | * | 0.001 | 0.001 |
| Income * outdegree | 0.001 | | -0.001 | 0.001 |
| Conflict * indegree | -0.005 | *** | -0.019 | -0.003 |
| Conflict * outdegree | 0.005 | | -0.006 | 0.015 |

P-value thresholds (two sided): + < 0.1, * < 0.05, ** < 0.001

**APPENDIX A.3.8**
**Degeneracy Check for TERGM in Table 3.5 (large P-values are desirable)**

```
Degeneracy check for network 1:
                              obs      sim       est       se  zval pval
ctriple                    1014.0     1279    265.25   794.35  0.33 0.74
ttriple                    4014.0     5809   1795.43  2643.48  0.68 0.50
mutual                      126.0      138     12.11    50.16  0.24 0.81
edgecov.delrecip[[1]]       246.0      257     10.97    54.29  0.20 0.84
edgecov.mem.stability[[1]]  243.0      206    -36.91   103.20 -0.36 0.72
idegreepopularity          1898.2     2306    407.37   599.90  0.68 0.50
odegreepopularity          1640.2     1914    273.77   439.48  0.62 0.53
absdiff.odegsqrt             87.1      102     15.05    30.06  0.50 0.62
nodematch.region            132.0      123     -9.46   166.89 -0.06 0.95
nodematch.language          247.0      277     30.25    50.91  0.59 0.55
nodeicov.aici            228455.5   277196  48740.95 47625.63  1.02 0.31
nodeocov.aici            220833.5   263996  43162.59 46410.09  0.93 0.35
nodeicov.conflict           497.0     1664   1167.48  1397.83  0.84 0.40
nodeocov.conflict           459.0     1992   1532.91  1753.52  0.87 0.38
edges                       439.0      487     48.36    83.04  0.58 0.56
Degeneracy check for network 2:
                              obs      sim       est       se  zval pval
ctriple                     926.0     1279    353.25   794.35  0.44 0.66
ttriple                    3994.0     5809   1815.43  2643.48  0.69 0.49
mutual                      118.0      138     20.11    50.16  0.40 0.69
edgecov.delrecip[[2]]       252.0      257      4.97    54.29  0.09 0.93
edgecov.mem.stability[[2]]  184.0      206     22.09   103.20  0.21 0.83
idegreepopularity          1916.2     2306    389.35   599.90  0.65 0.52
odegreepopularity          1653.6     1914    260.33   439.48  0.59 0.55
absdiff.odegsqrt             95.1      102      6.99    30.06  0.23 0.82
nodematch.region            131.0      123     -8.46   166.89 -0.05 0.96
nodematch.language          264.0      277     13.25    50.91  0.26 0.79
nodeicov.aici            254297.5   277196  22898.95 47625.63  0.48 0.63
nodeocov.aici            240513.0   263996  23483.09 46410.09  0.51 0.61
nodeicov.conflict          1666.0     1664     -1.52  1397.83  0.00 1.00
nodeocov.conflict          1676.0     1992    315.91  1753.52  0.18 0.86
edges                       442.0      487     45.36    83.04  0.55 0.58
Degeneracy check for network 3:
                              obs      sim       est       se  zval pval
ctriple                    1014.0     1279    265.25   794.35  0.33 0.74
ttriple                    4000.0     5809   1809.43  2643.48  0.68 0.49
mutual                      133.0      138      5.11    50.16  0.10 0.92
edgecov.delrecip[[3]]       247.0      257      9.97    54.29  0.18 0.85
edgecov.mem.stability[[3]]  184.0      206     22.09   103.20  0.21 0.83
idegreepopularity          1906.5     2306    399.03   599.90  0.67 0.51
odegreepopularity          1721.4     1914    192.54   439.48  0.44 0.66
absdiff.odegsqrt             96.1      102      6.03    30.06  0.20 0.84
nodematch.region            145.0      123    -22.46   166.89 -0.13 0.89
nodematch.language          262.0      277     15.25    50.91  0.30 0.76
nodeicov.aici            272842.0   277196   4354.45 47625.63  0.09 0.93
nodeocov.aici            260800.0   263996   3196.09 46410.09  0.07 0.95
nodeicov.conflict          2136.0     1664   -471.52  1397.83 -0.34 0.74
nodeocov.conflict          3287.0     1992  -1295.09  1753.52 -0.74 0.46
edges                       454.0      487     33.36    83.04  0.40 0.69
```

# APPENDIX A.3.9
## Robustness Check: Stochastic Actor-oriented Models

In order to test if the inferential results regarding the two hypotheses of this study were robust, I conducted analyses based on a different thresholding rule (based on actual flow size instead of top destinations of each country), and a differential inferential technique (stochastic actor-oriented models – SAOM – instead of TERG models). As shown below, results are qualitatively similar to the ones reported in the Chapter 3. For a detailed explanation of the stochastic actor oriented model see Snijders et al. (2010).

**SAOM to Investigate International Migration Flows in the Americas (1960-2000). Thresholding = Keep All Flows of Size > 10**

|  | Estimates |  | S.E. |
|---|---|---|---|
| **Intercept/edges** | -2.042 | ** | 0.414 |
| **Endogenous dependencies** |  |  |  |
| **Transitive triangles** | 0.080 | ** | 0.006 |
| **Cyclic triangles** | -0.027 | ++ | 0.015 |
| **Endogenous controls** |  |  |  |
| **In-degree popularity** | 0.421 | ** | 0.047 |
| **Out-degree popularity** | -0.360 | * | 0.147 |
| **Mutuality** | 0.634 | ** | 0.102 |
| **Exogenous controls** |  |  |  |
| **Same region** | 0.659 | ** | 0.085 |
| **Same language** | 0.379 | ** | 0.065 |
| **Income * alter** | 0.097 |  | 0.305 |
| **Income * ego** | 0.726 | * | 0.242 |
| **Conflict * alter** | -0.010 | ** | 0.002 |
| **Conflict * ego** | -0.004 | * | 0.002 |
| **Network rate function** |  |  |  |
| **Network rate period 1** | 12.222 | ** | 1.332 |
| **Network rate period 2** | 24.378 | ** | 3.728 |
| **Network rate period 3** | 25.396 | ** | 4.061 |
| **Overall Maximum Convergence Ratio  0.098** |  |  |  |

P-values: ++ (one-sided, $p < 0.05$); + (two-sided, $p < 0.1$); * (two-sided, $p < 0.05$); ** (two-sided, $p < 0.001$)

**SAOM to Investigate International Migration Flows in the Americas, 1960-2000.**
**Thresholding = Keep All Flows of Size > 50**

| | Estimates | | S.E. |
|---|---|---|---|
| Intercept/edges | -2.767 | ** | 0.565 |
| **Endogenous dependencies** | | | |
| Transitive triangles | 0.104 | ** | 0.010 |
| Cyclic triangles | -0.071 | * | 0.023 |
| **Endogenous controls** | | | |
| In-degree popularity | 0.322 | ** | 0.072 |
| Out-degree popularity | -0.040 | | 0.224 |
| Mutuality | 0.800 | ** | 0.114 |
| **Exogenous controls** | | | |
| Same region | 0.745 | ** | 0.110 |
| Same language | 0.376 | ** | 0.077 |
| Income * alter | 0.037 | | 0.443 |
| Income * ego | 0.839 | * | 0.332 |
| Conflict * alter | -0.012 | * | 0.004 |
| Conflict * ego | -0.005 | ++ | 0.003 |
| **Network rate function** | | | |
| Network rate period 1 | 8.250 | ** | 0.857 |
| Network rate period 2 | 13.879 | ** | 1.578 |
| Network rate period 3 | 17.095 | ** | 2.108 |
| **Overall Maximum Convergence Ratio 0.096** | | | |

P-values: ++ (one-sided, $p < 0.05$); + (two-sided, $p < 0.1$); * (two-sided, $p < 0.05$); ** (two-sided, $p < 0.001$)

**SAOM to Investigate International Migration Flows in the Americas, 1960-2000. Thresholding = Keep All Flows of Size > 100**

|  | Estimates | | S.E. |
|---|---|---|---|
| **Intercept/edges** | -3.203 | ** | 0.690 |
| **Endogenous dependencies** | | | |
| **Transitive triads** | 0.133 | ** | 0.016 |
| **Cyclic triads** | -0.121 | ** | 0.037 |
| **Endogenous controls** | | | |
| **In-degree popularity** | 0.301 | ** | 0.093 |
| **Out-degree popularity** | -0.104 | | 0.292 |
| **Mutuality** | 1.021 | ** | 0.135 |
| **Exogenous controls** | | | |
| **Same region** | 0.803 | ** | 0.136 |
| **Same language** | 0.392 | ** | 0.091 |
| **Income * alter** | 0.241 | | 0.493 |
| **Income * ego** | 0.821 | + | 0.422 |
| **Conflict * alter** | -0.012 | * | 0.005 |
| **Conflict * ego** | -0.006 | | 0.004 |
| **Network rate function** | | | |
| **Network rate period 1** | 6.797 | | 0.762 |
| **Network rate period 2** | 10.431 | | 1.213 |
| **Network rate period 3** | 12.276 | | 1.372 |
| **Overall Maximum Convergence Ratio  0.085** | | | |

++ (one-sided p < 0.05); + (two-sided p < 0.1); * (two-sided p < 0.05); ** (two-sided p < 0.001)

# APPENDIX A.3.10
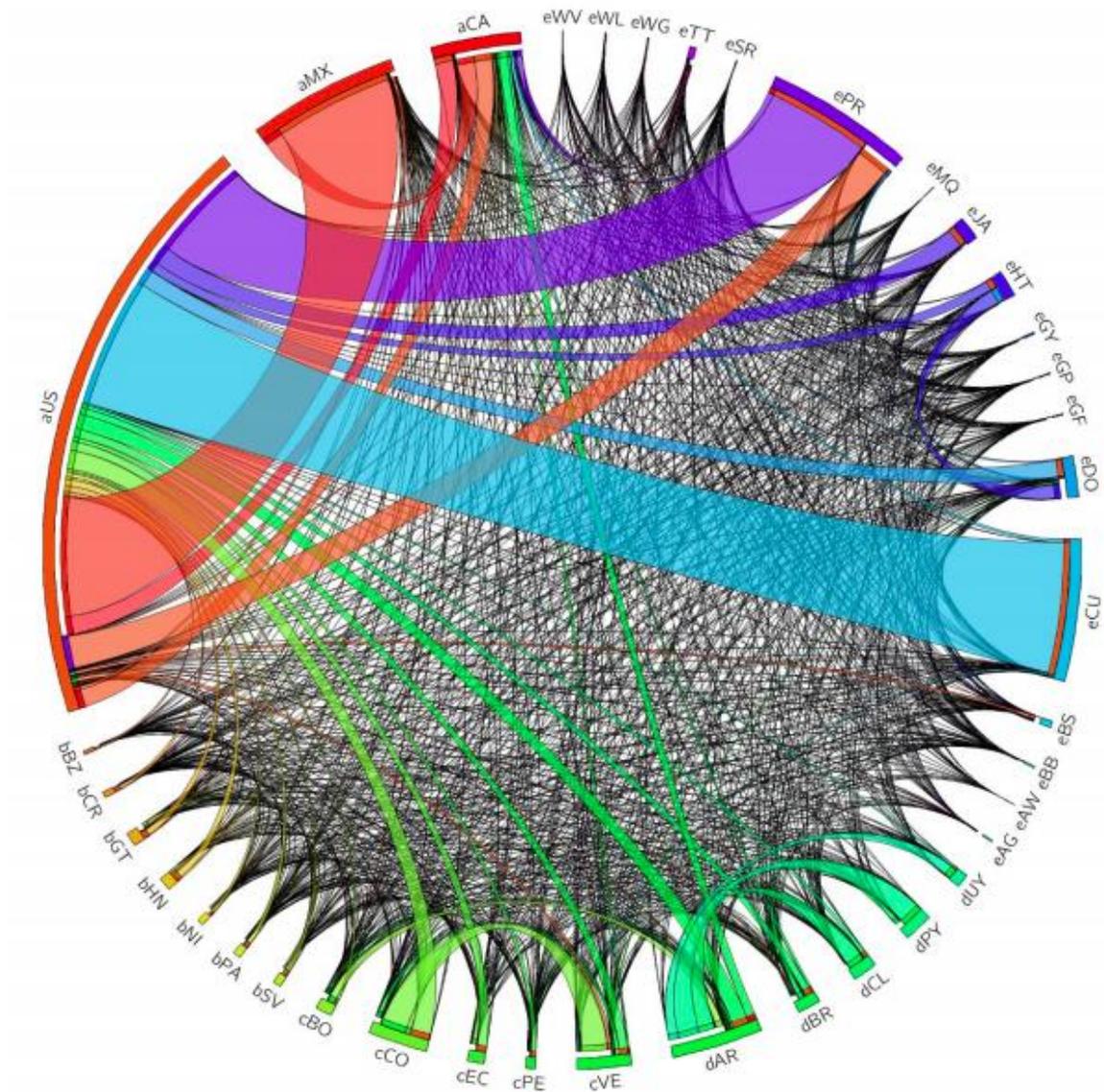## Circlos Plots Including the US

**1960s**



**Note.** Countries can be identified as follows: Canada (aCA); Mexico (aMX); United States (aUS); Belize (bBZ); Costa Rica (bCR); El Salvador (bSV); Guatemala (bGT); Honduras (bHN); Nicaragua (bNI); Panama (bPA); Bolivia (cBO); Colombia (cCO); Ecuador (cEC); Peru (cPE); Venezuela (cVE); Argentina (dAR); Brazil (dBR); Chile (dCL); Paraguay (dPY); Uruguay (dUY); Antigua and Barbuda (eAG); Aruba (eAW); the Bahamas (eBS); Barbados (eBB); Cuba (eCU); Dominican Republic (eDO); French Guiana (eGF); Grenada (eWG); Guadalupe (eGP); Guyana (eGY); Haiti (eHT); Jamaica (eJA); Martinique (eMQ); Puerto Rico (ePR); St. Lucia (eWL); St. Vincent and the Grenadines (eWV); Suriname (eSR); Trinidad and Tobago (eTT).

177

**1970s**



**Note.** Countries can be identified as follows: Canada (aCA); Mexico (aMX); United States (aUS); Belize (bBZ); Costa Rica (bCR); El Salvador (bSV); Guatemala (bGT); Honduras (bHN); Nicaragua (bNI); Panama (bPA); Bolivia (cBO); Colombia (cCO); Ecuador (cEC); Peru (cPE); Venezuela (cVE); Argentina (dAR); Brazil (dBR); Chile (dCL); Paraguay (dPY); Uruguay (dUY); Antigua and Barbuda (eAG); Aruba (eAW); the Bahamas (eBS); Barbados (eBB); Cuba (eCU); Dominican Republic (eDO); French Guiana (eGF); Grenada (eWG); Guadalupe (eGP); Guyana (eGY); Haiti (eHT); Jamaica (eJA); Martinique (eMQ); Puerto Rico (ePR); St. Lucia (eWL); St. Vincent and the Grenadines (eWV); Suriname (eSR); Trinidad and Tobago (eTT).

**1980s**



Note. Countries can be identified as follows: Canada (aCA); Mexico (aMX); United States (aUS); Belize (bBZ); Costa Rica (bCR); El Salvador (bSV); Guatemala (bGT); Honduras (bHN); Nicaragua (bNI); Panama (bPA); Bolivia (cBO); Colombia (cCO); Ecuador (cEC); Peru (cPE); Venezuela (cVE); Argentina (dAR); Brazil (dBR); Chile (dCL); Paraguay (dPY); Uruguay (dUY); Antigua and Barbuda (eAG); Aruba (eAW); the Bahamas (eBS); Barbados (eBB); Cuba (eCU); Dominican Republic (eDO); French Guiana (eGF); Grenada (eWG); Guadalupe (eGP); Guyana (eGY); Haiti (eHT); Jamaica (eJA); Martinique (eMQ); Puerto Rico (ePR); St. Lucia (eWL); St. Vincent and the Grenadines (eWV); Suriname (eSR); Trinidad and Tobago (eTT).
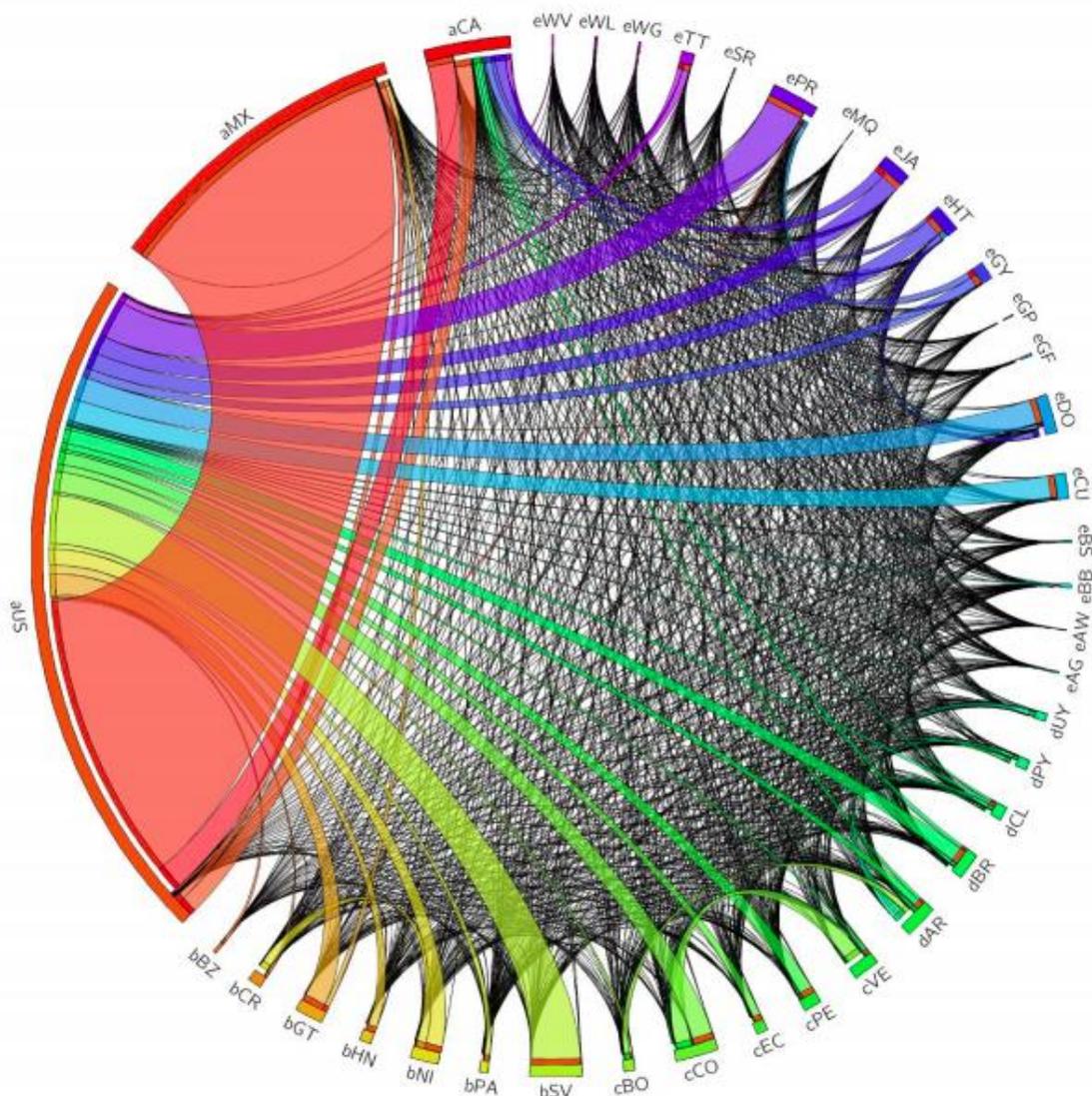
**1990s**



Note. Countries can be identified as follows: Canada (aCA); Mexico (aMX); United States (aUS); Belize (bBZ); Costa Rica (bCR); El Salvador (bSV); Guatemala (bGT); Honduras (bHN); Nicaragua (bNI); Panama (bPA); Bolivia (cBO); Colombia (cCO); Ecuador (cEC); Peru (cPE); Venezuela (cVE); Argentina (dAR); Brazil (dBR); Chile (dCL); Paraguay (dPY); Uruguay (dUY); Antigua and Barbuda (eAG); Aruba (eAW); the Bahamas (eBS); Barbados (eBB); Cuba (eCU); Dominican Republic (eDO); French Guiana (eGF); Grenada (eWG); Guadalupe (eGP); Guyana (eGY); Haiti (eHT); Jamaica (eJA); Martinique (eMQ); Puerto Rico (ePR); St. Lucia (eWL); St. Vincent and the Grenadines (eWV); Suriname (eSR); Trinidad and Tobago (eTT).
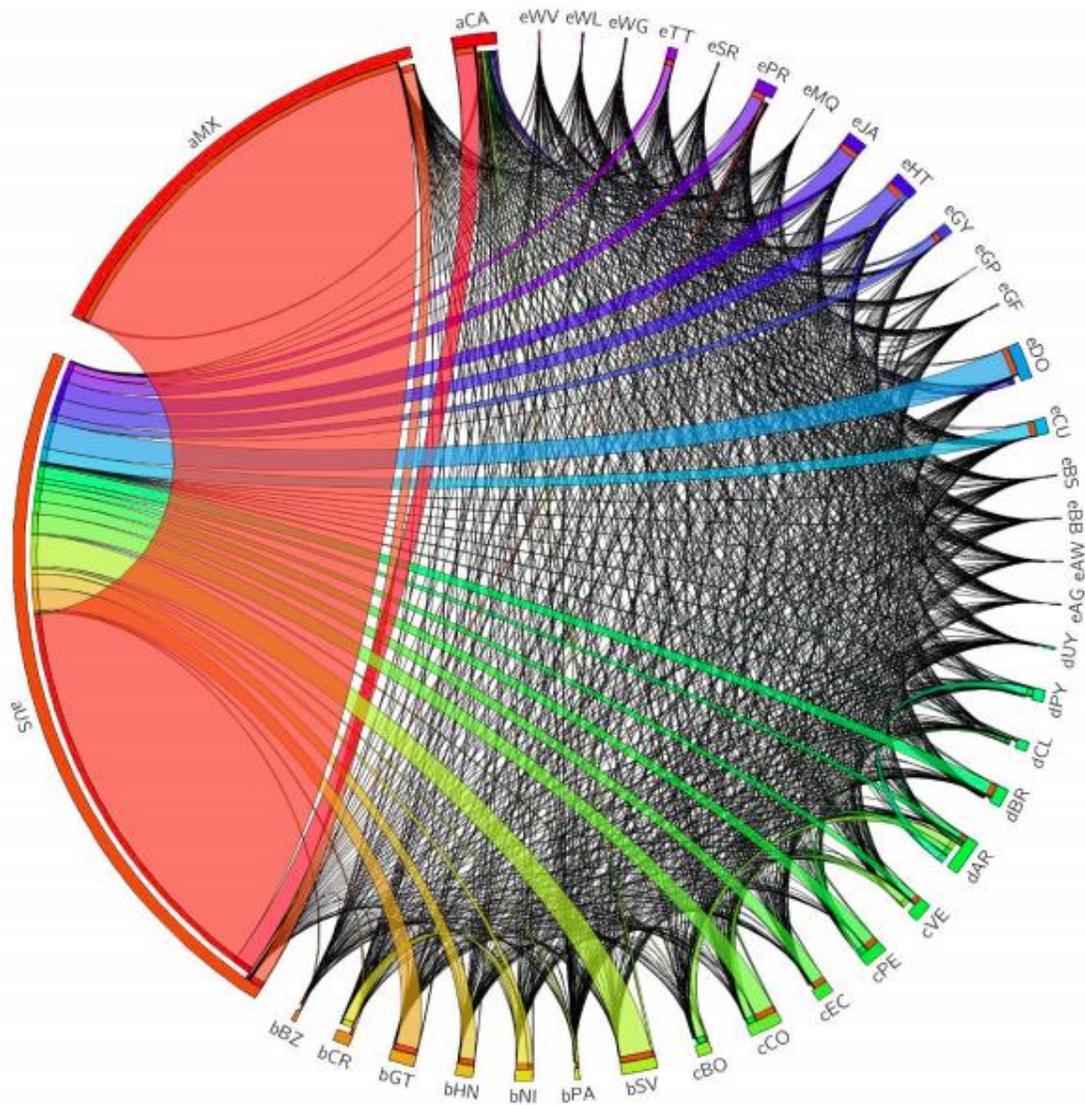
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